Universitat Autònoma de Barcelona

Efficiency of management in public schools. Analysis in a context of budgetary restrictions

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International Doctorate on Entrepreneurship and Management (IDEM)
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DOCTORAL THESIS

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To my family and my husband,

for their unconditional love,

help and comprehension.

ABSTRACT

This thesis is concerned about the development of innovative models for the assessment and monitoring of performance using non-parametric efficiency approaches such as Data Envelopment Analysis, conditional order-*m,* and Malmquist Total Factor Productivity Change Index. The models are applied to the evaluation of public schools performance in Catalonia (northeast Spain) with the aim of promoting the efficiency of the public education sector following different empirical approaches and bearing in mind the economic context. The empirical part of the thesis contributes to the definition of better public policies through the identification of best practice examples and areas with more potential for improvements.

The thesis includes four main research topics. The first topic discusses how to implement changes in the public education network in order to adapt resources to the allocated budget without losing outputs. This chapter presents an alternative model to globally assess the efficiency of the public education network and to reallocate human resources. The empirical approach is based on an extension of the Centralized Data Envelopment Analysis. Then, an iterative procedure capable of reallocating resources without jeopardizing the level of efficiency is proposed.

The second topic analyzes the impact of environmental factors on students' achievement by using a robust conditional order-*m* efficiency approach. In this chapter we develop two efficiency estimations, namely unconditional and conditional models, and then non-parametric regressions are done to disentangle the effect of environmental factors on school performance.

The third topic provides evidence on strategic interaction among public schools. It employs a two-stage estimation procedure to assess whether competition among public schools influences the demand for places in them. A robust conditional order-*m* approach is used to estimate the efficiency of each school. Subsequently, a spatial econometric framework is applied to explain the correlation in the demand for places due to the existence of strategic interaction.

The last topic develops a framework to assess the effectiveness and efficiency of a specific quality improvement program recently applied in public schools in Catalonia.

To do that, the differences-in-differences approach together with Malmquist total factor productivity change index is applied.

Overall, this thesis contributes to the development of robust tools to assess and promote the quality of education provided by public institutions, with a view to foster the efficiency and equity within the system.

Keywords: Conditional order-*m,* DEA, education, efficiency, environmental factors, impact evaluation, input-output analysis, Malmquist, public schools, reallocation, school choice, spatial econometrics.

JEL codes: C14, C21, C61, C67, H52, I21.

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ACRONYMS

CDEA: Centralized Data Envelopment Analysis

DEA: Data Envelopment Analysis

DiD: Differences-in-Differences

DMU: Decision Making Unit

EC: Efficiency Change

EU: European Union

FDH: Free Disposal Hull

GDP: Gross Domestic Product

IRS: Increasing Returns to Scale

NPM: New Public Management

MI: Malmquist Index

OECD: Organisation for Economic Co-operation and Development

PPS: Production Possibility Set

PSM: Propensity Score Matching

REA: Regional Educational Authority

SAR: Spatial Autocorrelation regression

SEM: Spatial Error Model

SFA: Stochastic Frontier Analysis

TC: Technological Change

TFPC: Total Factor Productivity Change

VRS: Variable Returns to Scale

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CHAPTER 1.

INTRODUCTION

1. INTRODUCTION

1.1 General context and motivation

In order to survive over time, organizations are advised to periodically review their management and the accomplishment of their objectives. This assessment, however, is frequently flawed due to the complex nature of the relationship between the resources used and the results obtained. Therefore, organizations are continually adapting themselves to new demands and market changes. In this environment, it is worth reviewing whether or not the conditions of survival are sufficiently guaranteed.

The economic reality in Spain is currently the subject of much debate. In the public sector, the pressure to contain spending means that, under current budgetary constraints, the continuity of public institutions constitutes a decision variable (Bel *et al.,* 2010). Likewise, the way public funding is spent is more closely scrutinized in times of austerity. At this juncture, any action aimed at assessing efficiency in the public sector is a priority of economic policy. An efficiency assessment in any public service must take into account the specific characteristics of the production process in the public domain, which is different from the private sector. As a result, techniques for efficiency measurement such as Data Envelopment Analysis (DEA) have become commonly used analytical tools. DEA can easily handle multiple dimensions of performance and is less vulnerable to the misspecification problems that can affect econometric models (Worthington, 2001).

Given this economic scenario, and the need to assess the efficiency of management in all types of organizations, including public services, the main objective of this thesis is to perform a multidimensional assessment of the efficiency of management in a specific public organization that is particularly difficult to manage: public education institutions.

Several reasons motivate the choice of public education institutions, particularly primary schools, for the development of this thesis. First and foremost, it is the availability of data. As discussed below in Section 1.3, we only have information from public schools. In Catalonia, and Spain in general, it is truly arduous to get access to public statistics containing rich information about sectors such as education or health. For this reason mainly, we restrict the empirical analysis of this thesis to public schools. Despite this limitation, we can confirm that our sample is representative, not only because it represents more than 74% of all institutions in the education network, but also because of the weight of public institutions in the education sector in general over time. As shown in Table 1.1, around 75% of primary schools are public in Spain, and 73% in the particular case of Catalonia.

Table 1.1. Share of public and private primary schools*[1]

	Year	Category	Spain	Catalonia	Barcelona	Girona	Lleida	Tarragona
Primary education	2009/ 2010	Total	13,831	2,274	1,464	270	245	295
		Public	10,375	1,665	964	229	219	253
		Private	3,456	609	500	41	26	42
		Share public	0.750	0.732	0.658	0.848	0.894	0.858
		Share private	0.250	0.268	0.342	0.152	0.106	0.142
	2010/ 2011	Total	13,880	2,302	1,484	277	244	297
		Public	10,398	1,694	985	236	218	255
		Private	3,482	608	499	41	26	42
		Share public	0.749	0.736	0.664	0.852	0.893	0.859
		Share private	0.251	0.264	0.336	0.148	0.107	0.141
	2011/ 2012	Total	13,895	2,312	1,488	279	248	297
		Public	10,406	1,701	986	238	222	255
		Private	3,489	611	502	41	26	42
		Share public	0.749	0.736	0.663	0.853	0.895	0.859
		Share private	0.251	0.264	0.337	0.147	0.105	0.141
	2012/ 2013	Total	13,908	2,327	1,504	280	246	297
		Public	10,413	1,715	1,000	239	221	255
		Private	3,495	612	504	41	25	42
		Share public	0.749	0.737	0.665	0.854	0.898	0.859
		Share private	0.251	0.263	0.335	0.146	0.102	0.141
	2013/ 2014	Total	13,904	2,330	1,508	282	243	297
		Public	10,409	1,716	1,003	240	218	255
		Private	3,495	614	505	42	25	42
		Share public	0.749	0.736	0.665	0.851	0.897	0.859
		Share private	0.251	0.264	0.335	0.149	0.103	0.141
	2014/ 2015	Total	13,865	2,314	1,493	282	243	296
		Public	10,377	1,714	1,002	240	218	254
		Private	3,488	600	491	42	25	42
		Share public	0.748	0.741	0.671	0.851	0.897	0.858
		Share private	0.252	0.259	0.329	0.149	0.103	0.142

* Excluded those schools offering just special education.
Source: *Ministerio de Educación, Cultura y Deporte.*

[1] The tables and figures in this thesis were prepared by the authors. Further citations are omitted to enhance readability.

Overall, the percentage of private schools represents one-fourth of the education institutions in our country. With the exception of Barcelona, where the percentage is relatively higher (about 26% of private schools), the figures are even more favorable to public schools in the case of Lleida, Girona and Tarragona, where the private sector represents between 10% and 15% of primary schools.

Second, as we stablished before, to assess the efficiency in the public sector is becoming a priority of economic policy. Therefore, the necessity of conducting efficiency assessments in any category of public services, included the education sector, inspires us to conduct this multidimensional assessment in order to propose policy recommendations useful for guiding future reforms.

In recent decades, interest in efficiency in education has increased from both academics and education providers (Goldstein and Woodhouse, 2000). From the academic point of view, the research on school efficiency consists of empirical studies that attempt to estimate and quantify the educational and contextual factors that characterize an efficient school. Since its inception 50 years ago, this body of literature has brought findings that contribute to the knowledge and better understanding of the educational factors that influence students' development. It also provides useful information for public administration decision makers, and for implementating improvement programs in schools. These developments lead to higher levels of quality and equity in the education system.

Angel Gurria, OECD Secretary-General, states in the influential OECD 2013 report 'Education at a glance' that "*what matters more are the choices countries make in how to allocate* [public spending on education], *and the policies they design to improve the efficiency and relevance of the education they provide*" (OECD, 2013, p. 15). Since the pioneering work by Bessent and Bessent (1980), Charnes *et al.* (1978, 1981) and Bessent *et al.* (1982), efficiency in education has grown in importance. Education provision is considered efficient when those responsible for education institutions make the best use of available resources. In an inefficient system educational attainments can be increased for a given spending level, or educational resources can be decreased for a given educational attainment (Bessent and Bessent, 1980).

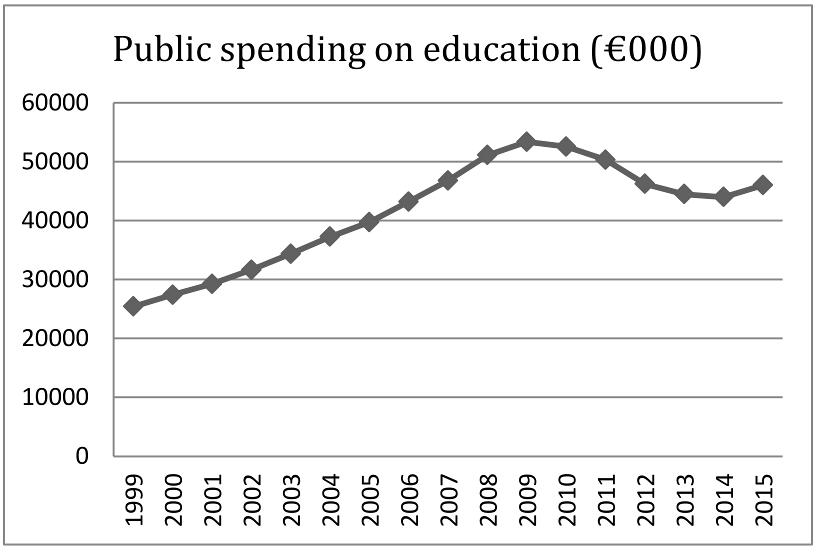
From the practitioners' point of view, efficiency in education is a topic of intense discussion among politicians, teachers, and other educational stakeholders. One of the reasons for the emergence of studies in this field is the increasing weight of the education sector in the economy (Eurostat, 2014). This sector fosters the intellectual training of the population, and improves human capital and labor productivity (Blau, 1996). As a result, more and better trained individuals have, on average, greater access and adaptation to the labor market. Thus, a country's investment in a quality education system is essential to ensure its development and economic growth (Hanushek and Kimko, 2000; Hanushek and Woessmann, 2008). Indeed, the trend in most OECD countries over the past decade has been to increase investment in education (OECD, 2013).

In the specific case of Spain, efforts were made to increase the level of investment in education up to 2009. However, these efforts were not been accompanied by successful education reforms or appropriate policies that would have improved educational outcomes. Spain continues to have a high dropout rate and occupies lower positions in various international evaluation programs such as PISA (*Program for International Student Assessment*), TIMSS (*Trends in International Mathematics and Science Study*) or PIRLS (*Progress in International Reading Literacy Study*). The lack of successful reforms, coupled with the effect of the economic and financial crisis, has led to a steady reduction in annual public spending allocated to education since 2010 (Figure 1.1).[2] The extent of these reductions has been such that by 2015 public expenditure on education had fallen to 2007 levels. In the past four years, more than 4,000 million euros have been cut through savings in teachers, classrooms, scholarships and fewer staff replacements on the one hand, and increased students-teacher ratios and teachers' school hours on the other. Constraints have also been made to transportation and school meal budgets. Not only have these measures provoked a strong social response, but they have also helped bring about an education system that fails to encourage good schools management.

[2] Law 14/2012, 20th April, on urgent measures to rationalize public spending on education (*Real Decreto Ley 14/2012, de 20 de Abril, de medidas urgentes de racionalización del gasto público en el ámbito educativo*).

Figure 1.1. Public spending on education in Spain

Year	Spending on education* (€000)
1999	25,428.0
2000	27,407.0
2001	29,237.2
2002	31,633.0
2003	34,349.6
2004	37,268.5
2005	39,732.8
2006	43,209.5
2007	46,790.8
2008	51,122.9
2009	53,374.9
2010	52,557.7
2011	50,343.9
2012	46,215.9
2013	44,493.6
2014	44,002.4
2015	46,003.6



* Financial expenses excluded.
Source: *Datos y Cifras, Ministerio de Educación, Cultura y Deporte. Spain*.

An overall assessment of efficiency is therefore needed to promote new ways of organizing and managing available resources, and to motivate schools to obtain good results efficiently. In other words, it is important to evaluate which public policies and practices might lead to increased educational efficiency with the available resources.

From the academic point of view, the advance in this line of research is becoming more interesting in light of the constantly growing number of publications and contributions, both theoretical and methodological, on efficiency in education (as evidenced in Chapter 2 of this thesis). Remarkable progress has been made in this field, due in part to the development of new methodologies that have improved the conceptualization and measurement of the factors that explain the educational attainment of both students and educational institutions (Johnson and Ruggiero, 2014). The approach proposed in this thesis represents an advance in the knowledge of this research line. Specifically, it aims to overcome the limitations in the literature and clearly contributes to improving performance in public education institutions, in accordance with their characteristics and the resources available to them. The results of this research have significant practical implications because the study prioritizes identifying the necessary measures to rationalize the use of scarce resources, making it possible to optimize the overall performance of the education system.

The broad empirical methodology of this thesis draws on non-parametric frontier analysis methods based on mathematical optimization models (such DEA and conditional order-*m* model) to analyze the efficiency of management in public schools. The public education sector provides an excellent context for efficiency assessment, as its institutions are non-profit, produce multiple outputs and there is an absence of output and input prices. Consequently, defining and estimating the production technology that students use to acquire knowledge is a complex task (Worthington, 2001; Johnes, 2015). These procedures are further explored in Chapter 2. Despite the growing interest and work in the field of performance assessment, robust tools to measure and guide improvements towards more efficient and sustainable educational institutions are less available. Therefore, more sophisticated and robust methods for performance assessment and benchmarking in this context are worth exploring.

This constitutes one of the contributions of the present thesis. This research aims to improve the current methods of efficiency assessment by exploring new methodologies, based on frontier techniques, which can effectively provide enhanced managerial information and guide education systems toward sustainable development and survival. Frontier methods have the advantage of allowing comparisons with the best observed performance by constructing a best practice frontier based on empirical data. From the alternative frontier methods available, in this thesis the use of non-parametric frontier methods such as DEA and conditional order-*m* model are explored in more detail due to their greater flexibility to incorporate the multidimensional nature of educational institutions, and the use of minimal assumptions on the shape of the best practice frontier.

The specific focus of this research is to assess, from different perspectives, efficiency in the management of resources available to public primary schools in Catalonia (north-east Spain). First, a centralized model of efficiency assessment that encourages good performance and good educational practices is applied. The introduction of incentives helps schools to be more efficient and allows them to survive over time (Burgess and Rato, 2003; Heinrich and Marschke, 2009). It constitutes a way of introducing domestic competition in the field of public education in the same way as in other public service organizations such as hospitals (Hafsteinsdóttir and Siciliani, 2012) or local authorities (Balaguer-Coll and Prior, 2009; Zafra-Gómez, *et al.,* 2012). Second, the research interest focuses on the role of exogenous factors on educational outcomes and the education system as a whole. Environment variables, represented by indicators related to the students' families or socio-economic status, have a significant effect on academic performance. However, the direction of this relationship is not always obvious. Third, an evaluation of schools' efficiency is performed taking into account their geographical location in order to identify spillover effects on educational results and demand for school places due to competition. Finally, a dynamic analysis is made of the effectiveness and efficiency in public school management, by assessing the impact of a program to improve educational quality. This analysis is supplemented with a study about the evolution of the total factor productivity change (TFPC) over the period the program was being implemented.

The objectives of this thesis are discussed in detail in the next section.

1.2 Research objectives and contributions

From a logical-deductive approach, the main objective of this thesis is to conduct a multidimensional assessment of the efficiency of management in public schools in Catalonia through the application of different non-parametric frontier techniques. In doing so, the current economic scenario of budget constraints in Spain is taken into account. Possibilities for improvement in management and in academic results are also established.

To perform this multidimensional assessment a number of specific objectives are posed. This section presents an overview of the research objectives and practical reasons that justify each goal.

1. To review the current state of the efficiency in education literature, and to analyze which variables and methods have been used so far.

The objective is to provide an extensive overview of the literature on efficiency in education summarizing the variables used in this field. We also review the frontier methodologies that have been applied to disentangle the efficiency of education institutions in previous analyses. Based on the insights from the literature review, some ways forward and conclusions are posed that serve as an agenda for future research. From this perspective, the research benefits since literature reviews are considered to play an important role in the development of a research field by summarizing published work in a specific area and offering new ideas. Ultimately, the areas outlined for further research could contribute to the development of future investigations.

2. To conduct a centralized efficiency assessment of public schools in order to propose a new design for the current education network to improve efficiency and competitiveness.

The aim is to implement a Centralized Data Envelopment Analysis (CDEA) to establish the level of overall efficiency of the public education network and to propose improvements for lower-performing schools. In turn, this objective also entails ranking schools by level of technical efficiency and redistributing scarce resources, making it possible to globally optimize the network performance without jeopardizing current levels of quality and academic attainment. The results provide useful information to help decision makers achieve a higher level of quality in education. To this end, a new school management model is proposed that motivates schools to obtain good results efficiently. Specifically, the public education budget is reorganized in order to reduce the public deficit through a simulation exercise.

3. To analyze the role of exogenous factors on students' academic results and school performance.

This objective focuses on the role exogenous factors play in educational outcomes. Although the literature on this topic is extensive, the direction of this relationship is not always obvious. Two order-*m* models (conditional and unconditional) are developed to estimate the efficiency of each school; non-parametric regressions are then performed to disentangle the effect of environmental factors on schools' performance.

This chapter contributes to the discussion by showing the effect of a specific set of environmental factors on school performance. In addition, some of these environmental factors have rarely been tested empirically and play a significant role in determining students' academic achievement. The interest of this goal is not only to contribute to the literature on efficiency in education and the effect of exogenous variables, but also to identify which part of the academic results is due to the school management and which part is due to exogenous conditions or non-controllable factors. As established in the specific objective analyzed above, there is an overall inefficiency in the education system because of the school management itself. However, in this third objective the research question focuses on analyzing whether or not there is also inefficiency due to external factors beyond the school's control, and what the direction of this relationship is.

4. To assess the effect of competition and location on efficiency and the demand for places in the school.

This goal supplements the previous two objectives by evaluating the efficiency of management including an additional level of analysis: school location. In this chapter, different schools' spatial effects are described and estimated through the application of spatial analysis. In fact, the schools efficiency analysis is based on various characteristics of the institution, the municipality or the educational area, and on different measures of educational performance.

Spatial models work with geo-referenced data such as coordinates in order to detect the presence of spillover effects like autocorrelation and spatial heterogeneity. To this end, several detection tests are applied. A spatial regression model is also designed that allows us to explain the demand for places in each school not only due to the efficient management of the institution or students' outcomes, but also to the presence of spatial effects and efficiency of management in neighboring schools (competition effect).

The results contribute to the literature by showing a significant effect of competition in location on public schools performance. The findings also reveal the differences between parents' choices when selecting a school due to the existence of competition.

5. To examine the effectiveness and efficiency of a program to improve educational quality on the academic performance of students and schools.

The final goal of this thesis complements the previous objectives by applying a dynamic analysis of the efficiency of management in public schools in Catalonia. To do so, after analyzing several factors that determine schools' efficiency in a given moment in time—such as the country's centralized educational system and budget reductions, exogenous factors, the location of the school, and the competition to attract the largest number of students—the next step is to conduct a longitudinal evaluation to see what changes have taken place over a given period during the implementation of a program to improve the quality of education provided. To do this, not only are the evolution of management efficiency and productivity analyzed, but an analysis is also made of the effectiveness in implementing an education program using impact evaluation methods that allow us to distinguish between correlation and causality.

Efficiency in education should not been seen as separate from effectiveness. Since the results of the education process are social constructs, there is always an effectiveness frontier, i.e., an acceptable level of the desired outcomes (e.g., quality, education attainments, equality of learning outcomes), which may be realized. Due to the social sensitivity of each education system, one should always bear in mind not only the simple link between what is invested in the system and the results of education, but also the balance between the dimensions of efficiency and effectiveness in creating education policy (OECD, 2006). This chapter contributes to both, the literature on efficiency in education (by conducting an analysis of efficiency over time) and the economics of education literature (by developing a model to assess the impact of an education program on students' outcomes).

1.3 Dataset

As stated in Section 1.2 the main objective of this thesis is to conduct a multidimensional assessment of the efficiency of management in public schools in Catalonia through the application of different non-parametric frontier techniques.

Catalonia is a region located in the north-east of Spain. It is a very densely populated and highly industrialized territory, leading the sector in Spain since the nineteenth century. It has the most important economy of the regions in Spain, generating 18.7% of Spanish GDP, on average. The case of the public education system in Catalonia is especially important for the study because, despite being traditionally one of the richest regions in Spain, it is also suffering severe cuts to its education budget.

As part of the Spanish education sector, the system in Catalonia has privately funded (private) and governmental funded (public) schools. Public schools are funded by the taxpayer and managed by Regional Educational Authorities (REAs). Private schools include both the purely private schools and the private grant-aided schools. The former are managed by private entities and funded by fees charged to the pupils. Private grant-aided schools belong to individual or legal entities but are financed with public funds allocated within a system of agreements regulated by the 1985 Right to Education Law.

As we stated in Section 1.1, the empirical analysis of this thesis is restricted to fully public schools mainly due to the lack of data from private schools on the one hand, and, on the other hand, because the real value of this thesis is to assess the efficiency of management in public schools from a multidimensional perspective to provide policy recommendations for future reforms in this sector. In addition, the analysis is focused on public primary education due to the connection with the above-mentioned research objectives. For instance, data on public schools are needed to correctly allocate the budget settled by the government and to reorganize human resources among schools to obtain a better and more efficient composition of the network. In addition, to conduct the spatial analysis in order to better explain the demand for places in public schools, data on primary schools is needed because it represents the starting point in the education process and the moment when parents decide which school is the best for their children. Moreover, the same data are necessary to assess the impact of the particular program to improve quality in education, since the main target of the program consists of public primary schools.

Public primary education in Catalonia is compulsory and free. It is divided into three two-year cycles. There are six academic courses, usually be taken between six and twelve years of age. At the end of this stage, students complete a test of basic skills in

Mathematics, Spanish, Catalan and a foreign language. The Evaluation Council of the Education System in Catalonia (*Consell Superior d'Avaluació del Sistema Educatiu*), and the relevant bodies of the education authorities collaborate in conducting a comprehensive diagnostic assessment of students. This evaluation takes place with students in the sixth year of primary education.

The data for this thesis come from the above-mentioned Evaluation Council of the Education System in Catalonia, the institution responsible for conducting the basic skill tests in the region. The Evaluation Council of the Education System is a consultancy division of the Department of Education, constituted in 1993 under the Law 305/93. The main objective of the Council is to analyze and evaluate the education system at its pre-primary, primary and secondary levels. The board comprises a president and a team of nine members, a secretary and a permanent management group, all of whom are highly-qualified experts. Additionally, a group of external advisors, including university professors, primary and secondary teachers and international experts in assessment, collaborate closely with the board. Apart from conducting the comprehensive diagnostic tests, the Council's main functions include:

- Issuing reports on whether or not the established educational objectives are attained according to current legislation.
- Generating reports and proposals which take into account the realities and perspectives of education systems in other countries and their respective assessment systems.
- Fostering dialogue on analogous experiences with similar institutions abroad.
- Establishing agreements with other organizations or institutions, both public and private, whose goals resemble those of the Evaluation Council of the Education System in Catalonia.
- Coordinating studies requested by the Evaluation Institute of the Spanish Ministry of Education.

The dataset covers five academic years, from 2009/2010 to 2013/2014, and contains information about a wide range of variables referring to the main determinants of educational achievement, represented by variables associated with students' achievement in the basic skill tests, information about the families and educational environment, as well as school management and educational supply. One of its main advantages is that it aggregates information about all students enrolled in each school, not a random sample of students, thereby avoiding the selection bias problem. The relevant unit of observation is the school.

In order to develop the objectives of this thesis, several variables are chosen following the economics of education literature at elementary and primary levels of education. Each chapter of the thesis details the selected variables for each case.

1.4 Thesis summary

The thesis is structured in seven chapters, which are briefly described in this section.

Chapter 2 presents an extensive overview of the literature on efficiency in education. It summarizes the inputs, outputs and contextual variables applied in previous studies, as well as the data sources used in papers in the field of efficiency in education. This chapter also reviews papers on education applying methodologies such as DEA, Malmquist Index (MI), Bootstrapping, robust frontiers, meta-frontier, or Stochastic Frontier Analysis (SFA). Based on the insights of the literature review, a second part of the chapter identifies some ways forward and practical directions for prospective researchers in the field.

Following the budget cuts detailed in Section 1.1, Chapter 3 proposes an alternative frontier model to analyze the overall efficiency of the primary public education system in Catalonia. To do so, an extension of the so-called CDEA that deals with non-transferable inputs is applied. This method has received less attention in the efficiency literature and evaluates the overall efficiency of a set of decision making units (DMUs) controlled by a central authority. In addition, a system is proposed to reallocate human resources in the public education network to obtain additional savings in the budget without jeopardizing the level of efficiency and quality of education provided.

As part of the (in)efficiency can be due to the existence of (bad) good environmental conditions, Chapter 4 analyzes the role of environmental factors on students' achievement by using a robust conditional order-*m* efficiency approach. This chapter develops two efficiency estimations, with and without considering environmental factors. Then non-parametric regressions are performed to disentangle the effect of environmental factors on performance.

Chapter 5 supplements previous chapters by including the school's location in the analysis. It provides evidence on the existence of strategic interaction among public schools. The public education market is not devoid of competition, which may be a result of schools' performance and location. This chapter employs a two-stage estimation procedure to assess whether competition among public schools and location influence the demand for places in them. Firstly, and following the empirical analysis of Chapters 3 and 4, a robust conditional order-*m* efficiency approach is used to estimate the performance of each school. Then a spatial econometric framework is applied to disentangle the correlation in the demand for school places due to the existence of strategic interaction (competition in performance and location).

Chapter 6 closes the empirical analysis of this thesis with a longitudinal analysis of the effectiveness and efficiency of public schools in the application of a specific quality improvement program in education. This program was implemented from the academic years 2010-11 to 2013-14. In view of the significant cuts made during the last years, this program aimed to improve students' educational outcomes (basic skills in different modules) and social cohesion, and to reduce absenteeism. The program also included the endowment of additional resources to schools for its implementation. The program is now finished; however, there is no empirical evidence available to assess its impact on schools' performance. The approach proposed in this chapter is new as it takes into account two kinds of analysis: effectiveness and efficiency. Specifically, the differences-in-differences (DiD) approach with panel data regressions together with a Malmquist TFPC index is applied.

Finally, Chapter 7 presents the conclusions and main contributions of the thesis, and suggestions for future research.

CHAPTER 2.

EFFICIENCY IN EDUCATION. A SYSTEMATIC REVIEW OF THE LITERATURE

2. EFFICIENCY IN EDUCATION. A SYSTEMATIC REVIEW OF THE LITERATURE

2.1 Introduction

As stated before in Section 1.2, the first specific objective of this thesis is to review the current state of the efficiency in education literature and to analyze which variables and methods have been used so far. This will help us define our variables and the methodological approach for the empirical chapters of this thesis (Chapters 3 to 6).

The way public funding is spent receives an increased attention in times of austerity. What is more important is the decision about how to allocate scarce resources and to conduct the suitable policies to foster the efficiency of the service provided. In particular, efficiency in education is a topic of intense debate among politicians, teachers, and other educational stakeholders. In addition to the increased awareness for public sector efficiency, the cost for education might be a reason for the interest of efficiency in education. On average, education becomes more expensive than other commodities (Eurostat, 2014). This interest has led to a growing literature on the efficiency of education (e.g. recently the paper by Johnes (2015) revises the operational research literature on education).

The education sector provides an excellent context for efficiency assessment as its institutions are non-profit, produce multiple outputs and there is an absence of output and input prices. Consequently, defining and estimating the production technology that students use to acquire knowledge is a complex task (Worthington, 2001; Johnes, 2015). The toolbox to study efficiency in education comprises non-parametric methods based on mathematical optimization models (such as DEA or FDH, e.g. Bradley *et al.,* 2010; Haelermans and De Witte, 2012), or parametric methods (such as SFA, e.g. Gronberg *et al.,* 2012; Grosskopf *et al.,* 2009).

This chapter discusses and summarizes educational efficiency literature in a structured way (detailing which inputs, outputs and environmental factors have been applied in previous empirical analysis) and provides methodological and practical steps forward. It is reviewed the literature on efficiency in education by covering articles that have applied frontier efficiency measurement techniques up to the year 2015. To do so, it is built further on the work of four previous papers that review this literature. The first one is the paper by Worthington (2001), who lists the papers that apply frontier techniques for measuring efficiency in education until 1998. Secondly, Johnes (2004) describes which techniques have been used for measuring efficiency and identifies the drawbacks and uses of applying different methods in the context of education. Then, Emrouznejad *et al.* (2008) collect the first 30 years of scholarly literature in the non-parametric frontier technique DEA, and lastly, Johnes (2015) discusses how operational research has been applied to education. The author provides an overview of the problems faced by government, managers and consumers of education, and the operational research techniques which have been applied to improve operations and provide solutions.

It should be noted that the purpose of this chapter is not to explain each methodological approach separately as a starting point for novice scholars in the field of efficiency in education. On the contrary, it is written in a way that allows summarizing which approaches have been used to study efficiency in education and shed light about new or more recent methods. In addition, it serves as a guide about the variables and research techniques applied in this thesis. There are standard textbooks which cover the explanation of several frontier methodologies for analyzing technical efficiency (for instance, Lovell (1993), Coelli *et al.* (2005) and Fried *et al.* (2008)). In summary this chapter aims to give an easy and quick overview of the literature, the selection of inputs, outputs and contextual variables, and some inspiration for further work.

The remainder of the chapter unfolds as follows. In Section 2.2 it is presented an extensive literature review on measuring efficiency in education from the perspective of operational research literature, while Section 2.3 concludes with some practical directions for further work in the field.

2.2 A systematic review on efficiency in education

2.2.1 Scope of review

For this review, we have used the search engines ERIC (*Educational Resources Information Center*) and WOS (*Web of Science*). On the one hand, ERIC is an online digital library of education research and information and is sponsored by the Institute of Education Sciences of the United States Department of Education. It provides a comprehensive, searchable, Internet-based bibliographic and full-text database of education research and information for educators, researchers, and the general public. On the other hand, WOS is the world's leading academic citation indexing database and search service, which is provided by Thomson Reuters. WOS covers the sciences, social sciences, arts and humanities and it provides bibliographic content and tools to access, analyze, and manage research information. It has a multidisciplinary coverage of over 10,000 high impact journals in science, social sciences, as well as international proceedings for over 120,000 conferences.

As a criterion for inclusion, we have pragmatically restricted the literature search to English language literature and we included empirical papers starting from 1977 until 2015. We decided to establish 1977 as the starting point given that this is the year when Aigner *et al.* (1977) published their seminal paper on SFA. Nevertheless, we might note that in 1978 Charnes *et al.* wrote the paper "Measuring the efficiency of decision making units" which became the seminal paper on DEA. These two years represent an interesting starting point from the survey of frontier efficiency measurement techniques in education. The descriptors and keywords "efficiency", "education", "frontier", "school", "performance measurement", "primary education", "higher education", "academic achievement", "educational assessment", "DEA", "SFA" and "economic of education" have been used in search for abstracts. Using these keywords, ERIC and WOS provided us with more than 250 papers. To limit the total number of hits, we also limited the search to those articles for which the full text was available. Finally, we obtained 223 papers.

The next subsections outline the main findings of this literature review from several angles. First, we discuss the different levels of analysis used to assess performance in education. Second, we discuss the main input/output variables specified in the education production literature at student, family, education institution and community level. Then, we revise another set of variables beyond internal control, namely non-discretionary (environmental) variables, which are determinants of educational achievement. Finally, we focus on which methodological approaches have been applied to study the efficiency of educational production. This extensive literature review might constitute an opportunity to derive more detailed indicators about education institutions' resources, results and environmental variables for future research.

2.2.2 Levels of analysis

Efficiency in education has been widely studied at various academic levels (see Table 2.1). Most studies focus either at the university level (89 studies in total), the school/high school level (58 studies in total), or the level of a district, county or city (44 in total). Only 9 studies were focused on the national level (country or multi-county). The latter is surprising as comparable national data sets (e.g. PISA, TIMSS, PIRLS) are increasingly available during the last few years. For future research, it seems very fruitful to undertake more research about differences across countries and education systems. Compared to the amount of papers at school/high school, university or district levels, there are few papers (i.e., only 23 papers) that focus on the student level. This is probably due to the lack of individual data in several countries. Finally, only two papers paid attention to the classroom level.

The majority of articles (143 in total) use national databases provided by the national Department of Education of each country (or similar agencies). Given the standardized way the databases are set up, this has the advantage that the data are less prone to measurement errors or diverging definitions (Table A1 in the Appendix classifies the origin of the databases used in the papers reviewed).

Table 2.1. Level of analysis

Business School, College, Department, Research Program, Researchers/University teachers, University levels studies
Taylor and Johnes (1989), Beasley (1990) (1995), Kao and Yang (1992), Johnes and Johnes (1993) (1995) (2009), Breu and Raab (1994), Sinuany-Stern *et al.* (1994), Johnes (1996), Mar-Molinero (1996), Athanassopoulos and Shale (1997), Madden *et al.* (1997), Cengiz and Yuki (1998), McMillan and Datta (1998), Sarrico and Dyson (2000), Thursby (2000), Ying and Sung (2000), Avkiran (2001), Korhonen *et al.* (2001), Abbott and Doucouliagos (2002) (2003) (2009), Izadi *et al.* (2002), Moreno and Tadepali (2002), Flegg *et al.* (2004), Cherchye and Vanden Abeele (2005), Emrouznejad and Thanassoulis (2005), Joumady and Ris (2005), Stevens (2005), Agasisti and Dal Bianco (2006) (2009), Bonaccorsi *et al.* (2006), Bougnol and Dulá (2006), Casu and Thanassoulis (2006), Giménez and Martínez (2006), Johnes (2006a) (2006b) (2006c) (2008) (2014), Koksal and Nalcaci (2006), McMillan and Chan (2006), Agasisti and Salerno (2007), Anderson *et al.* (2007), Fandel (2007), Tauer *et al.* (2007), Johnes *et al.* (2008), Johnes and Yu (2008), Kao and Hung (2008), Kuo and Ho (2008), Ray and Jeon (2008), Worthington and Lee (2008), Abramo and D'Angelo (2009), Agasisti and Johnes (2009) (2010) (2015), Cokgezen (2009), Colin-Glass *et al.* (2009), Tyagi *et al.* (2009), Agasisti and Pérez-Esparrells (2010), De Witte and Rogge (2010), Dehnokhalaji *et al.* (2010), Kantabutra and Tang (2010), Katharaki and Katharakis (2010), Kempkes and Pohl (2010), Rayeni and Saljooghi (2010), Agasisti *et al.* (2011) (2012), Johnes and Schwarzenberger (2011), Kounetas *et al.* (2011), Kuah and Wong (2011), Lee (2011), Thanassoulis *et al.* (2011), Wolszczak-Derlacz and Parteka (2011), Eff *et al.* (2012), Kong and Fu (2012), Sexton *et al.* (2012), Tochkov *et al.* (2012), Bayraktar *et al.* (2013), De Witte and Hudrlikova (2013), De Witte *et al.* (2013), Johnes (2013), Lu and Chen (2013), Zoghbi *et al.* (2013), Agasisti and Bonomi (2014), Duh *et al.* (2014), Mainardes *et al.* (2014), Mayston (2014), Nazarko and Saparauskas (2014).
Classroom, Course levels studies
Cooper and Cohn (1997), De Witte and Rogge (2011).
Council, County, District, City levels (municipality, Local Education Authorities, Province) levels studies
Butler and Monk (1985), Sengupta and Sfeir (1986) (1988), Jesson *et al.* (1987), Sengupta (1987), Smith and Mayston (1987), Mayston and Jesson (1988), Färe *et al.* (1989), Callan and Santerre (1990), Barrow (1991), Ganley and Cubbin (1992), McCarty and Yaisawarng (1993), Chalos and Cherian (1995), Ruggiero *et al.* (1995), Cubbin and Zamani (1996), Engert (1996), Ruggiero (1996a) (1996b) (2000) (2007), Bates (1997), Chalos (1997), Duncombe *et al.* (1997), Grosskopf *et al.* (1997) (1999) (2001) (2014), Heshmati and Kumbhakar (1997), Ray and Mukherjee (1998), Ruggiero and Bretschneider (1998), Ruggiero (1999), Ruggiero and Vitaliano (1999), Chakraborty *et al.* (2001), Grosskopf and Moutray (2001), Fukuyama and Weber (2002), Banker *et al.* (2004), Primont and Domazlicky (2006), Rassouli-Currier (2007), Denaux (2009), Davutyan *et al.* (2010), Houck *et al.* (2010), Naper (2010), Ouellette and Vierstraete (2010), Johnson and Ruggiero (2014).
School/high school levels studies
Bessent and Bessent (1980), Charnes *et al.* (1981), Bessent *et al.* (1982), Diamond and Medewitz (1990), Ray (1991), Deller and Rudnicki (1993), Bonesrønning and Rattsø (1994), Thanassoulis and Dunstan (1994), Jimenez and Paqueo (1996), Thanassoulis (1996), Kirjavainen and Loikkanen (1998), Mancebón and Bandrés (1999), Mancebón and Mar-Molinero (2000), McEwan and Carnoy (2000), Bradley *et al.* (2001) (2010), Daneshvary and Clauretie (2001), Muñiz (2002), Wang (2003), Kiong *et al.* (2005), Oliveira and Santos (2005), Ouellette and Vierstraete (2005), Waldo (2007b), Conroy and Arguea (2008), Cordero-Ferrera *et al.* (2008) (2010) (2015c), Mancebón and Muñiz (2008), Millimet and Collier (2008), Grosskopf *et al.* (2009), Hu *et al.* (2009), Kantabutra (2009), Sarrico and Rosa (2009), Alexander *et al.* (2010), Carpenter and Noller (2010), Essid *et al.* (2010) (2013) (2014), Khalili *et al.* (2010), Naper (2010), Sarrico *et al.* (2010), Agasisti (2011a) (2013), Mongan *et al.* (2011), Gronberg *et al.* (2012).

Table 2.1. Level of analysis (cont)

School/high school levels studies
Haelermans and Blank (2012), Haelermans and De Witte (2012), Haelermans *et al.* (2012), Johnes *et al.* (2012), Kirjavainen (2012), Mancebón *et al.* (2012), Misra *et al.* (2012), Portela *et al.* (2012), Burney *et al.* (2013), Haelermans and Ruggiero (2013), Aristovnik and Obadic (2014), Blackburn *et al.* (2014), Brennan *et al.* (2014).
Education system (country or multi-country) levels studies
Gershberg and Schuermann (2001), Hanushek and Luque (2003), Afonso and Aubyn (2006), Kocher *et al.* (2006), Giménez *et al.* (2007), Agasisti (2011b) (2014), Thieme *et al.* (2012), Aristovnik (2013).
Student level studies
Thanassoulis (1999), Colbert *et al.* (2000), Portela and Thanassoulis (2001), Robst (2001), Mizala *et al.* (2002), Thanassoulis and Portela (2002), Dolton *et al.* (2003), Johnes (2006b) (2006c), Waldo (2007a), Cherchye *et al.* (2010), De Witte *et al.* (2010), Portela and Camanho (2010), Cordero-Ferrera *et al.* (2011), Perelman and Santín (2011a) (2011b), Montoneri *et al.* (2012), De Witte and Kortelainen (2013), Deutsch *et al.* (2013), Portela *et al.* (2013), Thieme *et al.* (2013), Crespo-Cebada *et al.* (2014), Podinovski *et al.* (2014).

2.2.3 Determinants of efficiency in education

This section reviews the main variables used to assess efficiency in education through frontier methods. Starting from a production function, it is assumed that the education institution transforms inputs into outputs through a production process (Worthington, 2001). The educational production function represents the maximum output that can be achieved given the available resources and serves as a reference to calculate the inefficiency of those who fail to achieve it. In addition, the production function can be influenced by various factors which are beyond the control of the evaluated observation.

2.2.3.1 Input variables

To start with, in this subsection we review the discretionary inputs specified in the education production function (or those factors that are amenable to managerial control). To facilitate the explanation, we divide them into four categories: inputs at students' level, family-related variables, education institution and community variables.

Table 2.2 collects the inputs at student-level. From the psychological and behavioural variables, prior academic achievement has been broadly used (in 35 papers in total). It can be defined as exam success (Kuah and Wong, 2011), grade point average

(Cengiz and Yuki, 1998; Kong and Fu, 2012) or test scores (De Witte *et al.,* 2010; Portela and Camanho, 2010) in the previous academic year.

Table 2.2. Overview of inputs: student-related variables

Inputs	**Examples**
1. Psychological and behavioural variables	
Motivations/aspirations	Dolton *et al.* (2003), Perelman and Santín (2011a), Mainardes *et al.* (2014).
Peer group	Deller and Rudnicki (1993), Waldo (2007a), Cordero-Ferrera *et al.* (2011), Mongan *et al.* (2011), Perelman and Santín (2011a) (2011b), Crespo-Cebada *et al.* (2014), Grosskopf *et al.* (2014).
Predicted achievement	Grosskopf *et al.* (1997), (1999), Grosskopf and Moutray (2001).
Prior academic achievement	Bessent and Bessent (1980), Bessent *et al.* (1982), Färe *et al.* (1989), Diamond and Medewitz (1990), Breu and Raab (1994), Thanassoulis and Dunstan (1994), Johnes (1996) (2006a) (2006b) (2006c) (2014), Thanassoulis (1996), Athanassopoulos and Shale (1997), Cengiz and Yuki (1998), Colbert *et al.* (2000), Sarrico and Dyson (2000), Portela and Thanassoulis (2001), Fukuyama and Weber (2002), Thanassoulis and Portela (2002), Oliveira and Santos (2005), Primont and Domazlicky (2006), Waldo (2007a), Ray and Jeon (2008), De Witte *et al.* (2010), Khalili *et al.* (2010), Portela and Camanho (2010), Sarrico *et al.* (2010), Kuah and Wong (2011), Perelman and Santín (2011a), Kong and Fu (2012), Portela *et al.* (2012) (2013), Johnes (2013), Podinovski *et al.* (2014), Cordero *et al.* (2015c).
2. Demographic variables	
Disabilities (educational needs)	Bessent *et al.* (1982), Barrow (1991), Conroy and Arguea (2008), Grosskopf *et al.* (2009).
Free lunch/pay full lunch	Bessent *et al.* (1982), Barrow (1991), Thanassoulis and Dunstan (1994), Cooper and Cohn (1997), Mancebón and Mar-Molinero (2000), Bradley *et al.* (2001), Conroy and Arguea (2008).
Grants	Johnes and Johnes (1993) (1995), Thursby (2000), Ying and Sung (2000), Dolton *et al.* (2003), Conroy and Arguea (2008), Kuah and Wong (2011).
Age/Gender/Marital status	Diamond and Medewitz (1990), Cooper and Cohn (1997), Dolton *et al.* (2003), Johnes (2006b) (2006b), Mongan *et al.* (2011), Perelman and Santín (2011a), Kong and Fu (2012), Thieme *et al.* (2013).
Language background (limited English proficiency)	Sengupta and Sfeir (1988), Ganley and Cubbin (1992), Conroy and Arguea (2008), Grosskopf *et al.* (2009), Kirjavainen (2012), Mancebón *et al.* (2012).
Race/ethnicity/minority/ nationality	Bessent and Bessent (1980), Bessent *et al.* (1982), Sengupta and Sfeir (1986), Jesson *et al.* (1987), Sengupta (1987), Diamond and Medewitz (1990), Ganley and Cubbin (1992), Cooper and Cohn (1997), Heshmati and Kumbhakar (1997), Dolton *et al.* (2003), Johnes (2006b) (2006c), Conroy and Arguea (2008), Ray and Jeon (2008), Perelman and Santín (2011a), Mancebón *et al.* (2012).
Lifestyle	Johnes (1996) (2006b), Dolton *et al.* (2003), Hanushek and Luque (2003), Kong and Fu (2012).

About 8 scholars (such as Crespo-Cebada *et al.,* 2014) have used the peer group effect as an input to control for the characteristics of students' classmates. Lastly, some authors have taken into account variables like motivation or predicted achievement in this category (e.g. Dolton *et al.,* 2003 or Grosskopf and Moutray, 2001). The main demographic variables include the race/ethnicity/minority, and the presence of educational limitations as disabilities or language deficits. Although over the past few years the achievement gap between native and non-native youths is lower, it is still an active variable in the literature. Finally, only few papers have taken into account topics related to the lifestyle (exceptions are Dolton *et al.,* 2003; Johnes, 2006b; Kong and Fu, 2012).

An overview of family-related variables is presented in Table 2.3. Socio-economic status (27 papers) and parental education (20 papers) are the most widely used variables.

Table 2.3. Overview of inputs: family-related variables

Inputs	Examples
Economic needs	Bessent and Bessent (1980), Denaux (2009), Grosskopf *et al.* (2009), Sarrico and Rosa (2009), Sarrico *et al.* (2010), Mongan *et al.* (2011).
Family structure	Jesson *et al.* (1987), Smith and Mayston (1987), Bates (1997), Dolton *et al.* (2003), Perelman and Santín (2011a), Kirjavainen (2012).
Parental education	Charnes *et al.* (1981), Deller and Rudnicki (1993), Cooper and Cohn (1997), Heshmati and Kumbhakar (1997), Kirjavainen and Loikkanen (1998), McEwan and Carnoy (2000), Dolton *et al.* (2003), Hanushek and Luque (2003), Wang (2003), Conroy and Arguea (2008), Sarrico and Rosa (2009), Khalili *et al.* (2010), Sarrico *et al.* (2010), Cordero-Ferrera *et al.* (2011), Mongan *et al.* (2011), Perelman and Santín (2011a) (2011b), Kirjavainen (2012), Kong and Fu (2012), Mancebón *et al.* (2012).
Relationship with children	Thieme *et al.* (2013).
Resources available at home/internet use	Jesson *et al.* (1987), Ganley and Cubbin (1992), Cooper and Cohn (1997), Hanushek and Luque (2003), Mancebón and Muñiz (2008), Mongan *et al.* (2011), Perelman and Santín (2011a) (2011b), Mancebón *et al.* (2012), Aristovnik (2013), Deutsch *et al.* (2013), Thieme *et al.* (2013).
Socio-economic status (family income, employment)	Charnes *et al.* (1981), Smith and Mayston (1987), Sengupta and Sfeir (1988), Barrow (1991), Ganley and Cubbin (1992), Deller and Rudnicki (1993), Ruggiero (1996b), Thanassoulis (1996), Bates (1997), Cooper and Cohn (1997), Heshmati and Kumbhakar (1997), Mancebón and Bandrés (1999), Fukuyama and Weber (2002), Mizala *et al.* (2002), Dolton *et al.* (2003), Mancebón and Muñiz (2008), Denaux (2009), Kantabutra (2009), Agasisti (2011a) (2013), Cordero-Ferrera *et al.* (2011), Perelman and Santín (2011a), Kirjavainen (2012), Mancebón *et al.* (2012), Thieme *et al.* (2013), Crespo-Cebada *et al.* (2014), Podinovski *et al.* (2014).

The former is usually measured by parents' employment status or family income (e.g. Mancebón and Bandrés, 1999; Perelman and Santín, 2011a) and the latter is mentioned by many scholars as one of the key determinants of students' achievement (e.g. Hanushek and Luque, 2003; Kirjavainen, 2012). Some authors distinguish between mothers' and fathers' education in order to detect who exerts the greatest influence (e.g. Kong and Fu, 2012). In addition, family structure, parental support or involvement are also known as predictors of students' success (e.g. Dolton *et al*, 2003; Thieme *et al.,* 2013). Finally, resources available at home, or the extent to which children have reading material, computers, their own room or a place to study at home, have been found to be important determinants of educational outcomes (e.g. Mongan *et al.,* 2011, Deutsch *et al.,* 2013).

With respect to education institutions variables (see Table 2.4) the literature has paid attention to study the relationship between traditional educational inputs and educational outcomes. Typical inputs in the education production function are the characteristics of teachers (expenditures – 111 papers; number of personnel – 69 papers; experience, methods and salary – 70 papers, etc.) and the learning environment (size – 36 papers; organization and resources – 53 papers, etc.).

However, there exists no strong empirical evidence to support the notion that educational inputs have a significant positive influence on outcomes (Worthington, 2001). One may wonder whether these variables are appropriate to include in efficiency studies. There is still debate about the importance of including educational input in the analysis. For instance, Hanushek (2003, p. F91) claims that "*school resources are not closely related to student performance*". However, Mayston (1996) adds an altenative explanation for this finding. The author concludes that the observed levels of educational attainment and expenditure are themselves endogenously determined. Moreover, some of the 'popular' variables like class size have been extensively claimed in the economics of education literature to represent unproductive policy. Krueger (2003) states that results of quantitative summaries of the literature, such as Hanushek (1997), depend critically on whether studies are accorded equal weight. When studies are given equal weight, resources are systematically related to student achievement. When weights are in proportion to their number of estimates, resources and achievements are not systematically related. What matters is teacher quality, but this variable is difficult to capture.

Table 2.4. Overview of inputs: education institution variables

Inputs	Examples
Acceptance rate (selectivity)	Cengiz and Yuki (1998), Kirjavainen and Loikkanen (1998), Ray and Jeon (2008), Agasisti (2011b), Thieme *et al.* (2013).
Attendance rate	Bessent and Bessent (1980), Bessent *et al.* (1982), Chalos and Cherian (1995).
Climate	Bessent and Bessent (1980), Mongan *et al.* (2011), Perelman and Santín (2011a).
Dropout rate	Conroy and Arguea (2008), Mancebón *et al.* (2012).
Educational resources (books, building, computers, class, bus, grants)	Ruggiero *et al.* (1995), Jimenez and Paqueo (1996), Ruggiero (1996a) (1996b), Athanassopoulos and Shale (1997), Cooper and Cohn (1997), Heshmati and Kumbhakar (1997), Ruggiero and Bretschneider (1998), Ruggiero (2000), Thursby (2000), Moreno and Tadepali (2002), Emrouznejad and Thanassoulis (2005), Kiong *et al.* (2005), Agasisti and Dal Bianco (2006) (2009), Bonaccorsi *et al.* (2006), Bougnol and Dulá (2006), Johnes (2006a) (2008), Primont and Domazlicky (2006), Giménez *et al.* (2007), Tauer *et al.* (2007), Johnes and Yu (2008), Ray and Jeon (2008), Agasisti and Johnes (2009), Hu *et al.* (2009), Agasisti and Pérez-Esparrells (2010), Essid *et al.* (2010), Agasisti (2011a) (2011b) (2013), Agasisti *et al.* (2011) (2012), Cordero-Ferrera *et al.* (2011) (2015c), Lee (2011), Mongan *et al.* (2011), Perelman and Santín (2011a) (2011b), Haelermans and Blank (2012), Mancebón *et al.* (2012), Misra *et al.* (2012), Thieme *et al.* (2012) (2013), Haelermans and Ruggiero (2013), Zoghbi *et al.* (2013), Crespo-Cebada *et al.* (2014).
Enrollment (number of students)	Johnes (1996), Ruggiero and Vitaliano (1999), Grosskopf *et al.* (2001), Cherchye and Vanden Abeele (2005), Kiong *et al.* (2005), Fandel (2007), Agasisti and Dal Bianco (2009), Grosskopf *et al.* (2009), Sarrico and Rosa (2009), Alexander *et al.* (2010), Davutyan *et al.* (2010), Khalili *et al.* (2010), Katharaki and Katharakis (2010), Rayeni and Saljooghi (2010), Gronberg *et al.* (2012), Johnes *et al.* (2012), Misra *et al.* (2012), Aristovnik and Obadic (2014), Mayston (2014), Johnes (2014).
Expenditures (teaching, research, administrator, supporting staff)	Bessent and Bessent (1980), Bessent *et al.* (1982), Butler and Monk (1985), Sengupta and Sfeir (1986), Jesson *et al.* (1987), Sengupta (1987), Smith and Mayston (1987), Mayston and Jesson (1988), Färe *et al.* (1989), Beasley (1990), Callan and Santerre (1990), Diamond and Medewitz (1990), Barrow (1991), Ganley and Cubbin (1992), Deller and Rudnicki (1993), McCarty and Yaisawarng (1993), Breu and Raab (1994), Sinuany-Stern *et al.* (1994), Beasley (1995), Chalos and Cherian (1995), Ruggiero *et al.* (1995), Cubbin and Zamani (1996), Engert (1996), Jimenez and Paqueo (1996), Johnes (1996) (2006a) (2008) (2014), Ruggiero (1996a) (1999) (2000), Athanassopoulos and Shale (1997), Bates (1997), Chalos (1997), Duncombe *et al.* (1997), Grosskopf *et al.* (1997) (1999) (2014), Heshmati and Kumbhakar (1997), McMillan and Datta (1998), Mancebón and Bandrés (1999), Ruggiero and Vitaliano (1999), McEwan and Carnoy (2000), Daneshvary and Clauretie (2001), Gershberg and Schuermann (2001), Korhonen *et al.* (2001), Robst (2001), Abbott and Doucouliagos (2002) (2003), Fukuyama and Weber (2002), Izadi *et al.* (2002), Muñiz (2002), Banker *et al.* (2004), Flegg *et al.* (2004), Stevens (2005), Bonaccorsi *et al.* (2006), Casu and Thanassoulis (2006), Giménez and Martínez (2006), Kocher *et al.* (2006), McMillan and Chan (2006), Primont and Domazlicky (2006), Agasisti and Salerno, (2007), Anderson *et al.* (2007).

Table 2.4. Overview of inputs: education institution variables (cont)

Inputs	Examples
Expenditures (teaching, research, administrator, supporting staff)	Rassouli-Currier (2007), Conroy and Arguea (2008), Cordero-Ferrera *et al.* (2008) (2010), Johnes *et al.* (2008), Johnes and Yu (2008), Kao and Hung (2008), Kuo and Ho (2008), Millimet and Collier (2008), Worthington and Lee (2008), Agasisti and Johnes (2009) (2010) (2015), Denaux (2009), Hu *et al.* (2009), Johnes and Johnes (2009), Tyagi *et al.* (2009), Alexander *et al.* (2010), Carpenter and Noller (2010), Houck *et al.* (2010), Katharaki and Katharakis (2010), Kempkes and Pohl (2010), Ouellette and Vierstraete (2010), Johnes and Schwarzenberger (2011), Kounetas *et al.* (2011), Kuah and Wong (2011), Lee (2011), Mongan *et al.* (2011), Thanassoulis *et al.* (2011), Gronberg *et al.* (2012), Haelermans and Blank (2012), Haelermans and De Witte (2012), Haelermans *et al.* (2012), Kirjavainen (2012), Misra *et al.* (2012), Sexton *et al.* (2012), Aristovnik (2013), Essid *et al.* (2013) (2014), Haelermans and Ruggiero (2013), Johnes (2013), Lu and Chen (2013), Zoghbi *et al.* (2013), Agasisti (2014), Aristovnik and Obadic (2014), Blackburn *et al.* (2014), Brennan *et al.* (2014), Duh *et al.* (2014), Johnson and Ruggiero (2014), Mayston (2014).
Faculty to student ratio/number of faculties	Breu and Raab (1994), McMillan and Datta (1998), Colbert *et al.* (2000), Kocher *et al.* (2006), Ray and Jeon (2008), Ouellette and Vierstraete (2010).
Job satisfaction	Bessent and Bessent (1980), Misra *et al.* (2012).
Mobility index	Bessent and Bessent (1980), Conroy and Arguea (2008).
Ownership (public, private, charter)	Diamond and Medewitz (1990), Johnes (1996) (2006b) (2006c), Cooper and Cohn (1997), Thursby (2000), Mizala *et al.* (2002), Dolton *et al.* (2003), Carpenter and Noller (2010), Kantabutra and Tang (2010), Perelman and Santín (2011a), Kirjavainen (2012), Thieme *et al.* (2013), Agasisti and Johnes (2015).
Parental visit index	Charnes *et al.* (1981), Jimenez and Paqueo (1996), Conroy and Arguea (2008).
Personnel (Teachers - academic staff-, other staff - administrators or support staff) (FTE)	Bessent *et al.* (1982), Ray (1991), Johnes and Johnes (1993) (1995), Jimenez and Paqueo (1996), Mar-Molinero (1996), Ruggiero (1996b), Athanassopoulos and Shale (1997), Grosskopf *et al.* (1997) (1999) (2001) (2009), Madden *et al.* (1997), Ray and Mukherjee (1998), Ruggiero and Bretschneider (1998), Thursby (2000), Ying and Sung (2000), Avkiran (2001), Grosskopf and Moutray (2001), Abbott and Doucouliagos (2002) (2003) (2009), Fukuyama and Weber (2002), Moreno and Tadepali (2002), Muñiz (2002), Flegg *et al.* (2004), Agasisti and Dal Bianco (2006) (2009), Bonaccorsi *et al.* (2006), Bougnol and Dulá (2006), Johnes (2006a) (2008) (2014), Fandel (2007), Kao and Hung (2008), Millimet and Collier (2008), Worthington and Lee (2008), Abramo and D'Angelo (2009), Agasisti and Johnes (2009), Cokgezen (2009), Colin-Glass *et al.* (2009), Tyagi *et al.* (2009), Agasisti and Pérez-Esparrells (2010), Alexander *et al.* (2010), Bradley *et al.* (2010), Davutyan *et al.* (2010), Essid *et al.* (2010) (2013) (2014), Katharaki and Katharakis (2010), Kempkes and Pohl (2010), Ouellette and Vierstraete (2010), Rayeni and Saljooghi (2010), Agasisti *et al.* (2011) (2012), Kounetas *et al.* (2011), Kuah and Wong (2011), Lee (2011), Wolszczak-Derlacz and Parteka (2011), Haelermans and Blank (2012), Haelermans *et al.* (2012), Johnes *et al.* (2012), Thieme *et al.* (2012), Burney *et al.* (2013), Deutsch *et al.* (2013), Haelermans and Ruggiero (2013), Brennan *et al.* (2014), Duh *et al.* (2014), Mayston (2014).
Research income/tuition fees/outside funding	Beasley (1990), Breu and Raab (1994), Beasley (1995), Athanassopoulos and Shale (1997), Heshmati and Kumbhakar (1997), Cengiz and Yuki (1998), Ying and Sung (2000), Dolton *et al.* (2003), Koksal and Nalcaci (2006), Fandel (2007), Kempkes and Pohl (2010), Wolszczak-Derlacz and Parteka (2011).

Table 2.4. Overview of inputs: education institution variables (cont)

Inputs	Examples
Size (number of students, student per class, proportion of boys and girls)	Sengupta and Sfeir (1986) (1988), Sengupta (1987), Jimenez and Paqueo (1996), Johnes (1996), Athanassopoulos and Shale (1997), Heshmati and Kumbhakar (1997), Thursby (2000), Mizala *et al.* (2002), Hanushek and Luque (2003), Flegg *et al.* (2004), Agasisti and Dal Bianco (2006) (2009), Johnes (2006a) (2008), Koksal and Nalcaci (2006), Johnes and Yu (2008), Kao and Hung (2008), Ray and Jeon (2008), Worthington and Lee (2008), Agasisti and Johnes (2009), Agasisti and Pérez-Esparrells (2010), Bradley *et al.* (2010), Essid *et al.* (2010) (2013) (2014), Kounetas *et al.* (2011), Kuah and Wong (2011), Perelman and Santín (2011a), Wolszczak-Derlacz and Parteka (2011), Haelermans and Blank (2012), Kirjavainen (2012), Mancebón *et al.* (2012), Burney *et al.* (2013), Crespo-Cebada *et al.* (2014), Podinovski *et al.* (2014).
Student/teacher ratio (or vice versa)	Bessent and Bessent (1980), Charnes *et al.* (1981), Bessent *et al.* (1982), Ray (1991), McCarty and Yaisawarng (1993), Breu and Raab (1994), Chalos and Cherian (1995), Johnes (1996), Cooper and Cohn (1997), Heshmati and Kumbhakar (1997), Mancebón and Bandrés (1999), Mancebón and Mar-Molinero (2000), Chakraborty *et al.* (2001), Mizala *et al.* (2002), Afonso and Aubyn (2006), Primont and Domazlicky (2006), Cordero-Ferrera *et al.* (2008) (2010) (2015c), Johnes and Yu (2008), Denaux (2009), Hu *et al.* (2009), Kantabutra (2009), Cherchye *et al.* (2010), Naper (2010), Sarrico *et al.* (2010), Agasisti (2011a) (2011b) (2013) (2014), Perelman and Santín (2011b), Kirjavainen (2012), Misra *et al.* (2012), Johnes (2013), Zoghbi *et al.* (2013), Crespo-Cebada *et al.* (2014).
Teacher absences	Heshmati and Kumbhakar (1997).
Teacher age/gender/ race	Johnes (1996), Sarrico and Rosa (2009), Misra *et al.* (2012).
Teacher experience/ education	Bessent *et al.* (1982), Sengupta and Sfeir (1986), Färe *et al.* (1989), Diamond and Medewitz (1990), McCarty and Yaisawarng (1993), Bonesrønning and Rattsø (1994), Chalos and Cherian (1995), Jimenez and Paqueo (1996), Johnes 1996), Ruggiero (1996b), Cooper and Cohn (1997), Heshmati and Kumbhakar (1997), Cengiz and Yuki (1998), Kirjavainen and Loikkanen (1998), Ruggiero and Bretschneider (1998), Chakraborty *et al.* (2001), Mizala *et al.* (2002), Hanushek and Luque (2003), Kiong *et al.* (2005), Stevens (2005), Primont and Domazlicky (2006), Rassouli-Currier (2007), Waldo (2007a), Denaux (2009), Hu *et al.* (2009), Bradley *et al.* (2010), Sarrico *et al.* (2010), Agasisti *et al.* (2011) (2012), Kuah and Wong (2011), Misra *et al.* (2012), Thieme *et al.* (2012).
Teacher methods/ organization and management/ quality/innovati on	Bessent and Bessent (1980), Sengupta (1987), Kirjavainen and Loikkanen (1998), Mizala *et al.* (2002), Dolton *et al.* (2003), Oliveira and Santos (2005), Afonso and Aubyn (2006), Agasisti and Salerno, (2007), Giménez *et al.* (2007), Carpenter and Noller (2010), Cherchye *et al.* (2010), Dehnokhalaji *et al.* (2010), Sarrico *et al.* (2010), Haelermans and Blank (2012), Montoneri *et al.* (2012), Bayraktar *et al.* (2013), De Witte and Kortelainen (2013), Deutsch *et al.* (2013), Johnes (2013), Zoghbi *et al.* (2013), Nazarko and Saparauskas (2014).
Teacher salary	Butler and Monk (1985), Sengupta and Sfeir (1986) (1988), Sinuany-Stern *et al.* (1994), Ruggiero (1996a) (2000), Duncombe *et al.* (1997), Grosskopf *et al.* (1997) (1999) (2001), Ruggiero and Vitaliano (1999), Giménez and Martínez (2006), Koksal and Nalcaci (2006), Hu *et al.* (2009), Eff *et al.* (2012), Gronberg *et al.* (2012), Haelermans and Blank (2012), Johnson and Ruggiero (2014).

A fourth category of inputs that should be noted refers to community-related variables. Student attributes, institution features and family background cannot be viewed apart from the context in which they are embedded and by which they are influenced (De Witte *et al.,* 2013). While this category of variables has delivered by far fewer examples, it is very important to include them in the efficiency analysis. Inclusion can take the form of input variable, or as contextual variable. An overview of community variables included in papers as input variable is presented in Table 2.5. The geographical location (8 papers) and the number of education institutions in the area (4 papers) may have effects on students' performance, either directly or indirectly (McEwan and Carnoy, 2000). Neighborhood characteristics play also an important role. Youths living in disadvantaged environments may be more susceptible to fail (Grosskopf *et al.,* 2014). In addition, many other community variables like the proportion of household with school-aged children or how well educated the population in the neighborhood is, play a crucial role (Gershberg and Schuermann, 2001).

Table 2.5. Overview of inputs: community-related variables

Inputs	Examples
Competition (e.g. Herfindahl index, number of education institutions, location)	Grosskopf *et al.* (2001), Millimet and Collier (2008), Perelman and Santín (2011a), Nazarko and Saparauskas (2014).
Neighborhood characteristics (taxes, employment)	Ganley and Cubbin (1992), Grosskopf *et al.* (2001) (2014).
Percentage of households with school-aged children	Heshmati and Kumbhakar (1997).
Percentage of population with post-primary education	Gershberg and Schuermann (2001), Grosskopf *et al.* (2001), Wang (2003).
Urban/rural area (location)	Diamond and Medewitz (1990), Ganley and Cubbin (1992), Jimenez and Paqueo (1996), McEwan and Carnoy (2000), Grosskopf *et al.* (2001), Dolton *et al.* (2003), Kantabutra and Tang (2010), Kirjavainen (2012).

2.2.3.2 Output variables

There is a generally greater agreement among educational efficiency studies regarding the specification of outputs. The numbers of graduates, passing rates and average test scores have all been used as output measures in educational efficiency analysis (see Table 2.6). However, none of these measures is ideal. For example, the number of graduates (included in 80 papers) captures the quantity of educational output, but it does not capture the quality. Quality is better reflected in test scores (in 127 papers).

Table 2.6. Overview of outputs

Outputs	Examples
1. Student achievement	
Number of graduates / percentage passing	Butler and Monk (1985), Jesson *et al.* (1987), Smith and Mayston (1987), Mayston and Jesson (1988), Beasley (1990), Callan and Santerre (1990), Barrow (1991), McCarty and Yaisawarng (1993), Bonesrønning and Rattsø (1994), Sinuany-Stern *et al.* (1994), Beasley (1995), Cubbin and Zamani (1996), Johnes (1996) (2006a) (2006c) (2008), Mar-Molinero (1996), Athanassopoulos and Shale (1997), Heshmati and Kumbhakar (1997), Madden *et al.* (1997), Cengiz and Yuki (1998), Kirjavainen and Loikkanen (1998), Ray and Mukherjee (1998), Mancebón and Bandrés (1999), Ruggiero and Vitaliano (1999), Mancebón and Mar-Molinero (2000), Avkiran (2001), Grosskopf and Moutray (2001), Robst (2001), Abbott and Doucouliagos (2002) (2003) (2009), Izadi *et al.* (2002), Moreno and Tadepali (2002), Muñiz (2002), Flegg *et al.* (2004), Emrouznejad and Thanassoulis (2005), Stevens (2005), Agasisti and Dal Bianco (2006) (2009), Bonaccorsi *et al.* (2006), Kocher *et al.* (2006), Koksal and Nalcaci (2006), Anderson *et al.* (2007), Fandel (2007), Rassouli-Currier (2007), Cordero-Ferrera *et al.* (2008), Johnes *et al.* (2008), Kuo and Ho (2008), Mancebón and Muñiz (2008), Worthington and Lee (2008), Agasisti and Johnes (2009), Denaux (2009), Johnes and Johnes (2009), Kantabutra (2009), Sarrico and Rosa (2009), Agasisti and Pérez-Esparrells (2010), Alexander *et al.* (2010), Bradley *et al.* (2010), De Witte *et al.* (2010), Houck *et al.* (2010), Kantabutra and Tang (2010), Katharaki and Katharakis (2010), Kempkes and Pohl (2010), Khalili *et al.* (2010), Rayeni and Saljooghi (2010), Sarrico *et al.* (2010), Agasisti (2011b), Kuah and Wong (2011), Thanassoulis *et al.* (2011), Wolszczak-Derlacz and Parteka (2011), Misra *et al.* (2012), Burney *et al.* (2013), Haelermans and Ruggiero (2013), Johnes (2013), Lu and Chen (2013), Aristovnik and Obadic (2014), Duh *et al.* (2014), Grosskopf *et al.* (2014), Podinovski *et al.* (2014), Agasisti and Johnes (2015).
Students' test scores in different subjects (Reading, Languages, Math, Arts) / Students' performance	Bessent and Bessent (1980), Charnes *et al.* (1981), Bessent *et al.* (1982), Sengupta and Sfeir (1986) (1988), Jesson *et al.* (1987), Sengupta (1987), Smith and Mayston (1987), Mayston and Jesson (1988), Färe *et al.* (1989), Callan and Santerre (1990), Diamond and Medewitz (1990), Barrow (1991), Ray (1991), Ganley and Cubbin (1992), Deller and Rudnicki (1993), Breu and Raab (1994), Thanassoulis and Dunstan (1994), Chalos and Cherian (1995), Ruggiero *et al.* (1995), Cubbin and Zamani (1996), Engert (1996), Jimenez and Paqueo (1996), Johnes (1996) (2006b) (2006c), Ruggiero (1996a) (1996b) (1999) (2000), Thanassoulis (1996), Athanassopoulos and Shale (1997), Bates (1997), Chalos (1997), Cooper and Cohn (1997), Duncombe *et al.* (1997), Grosskopf *et al.* (1997) (1999) (2001) (2009) (2014), Kirjavainen and Loikkanen (1998), Ray and Mukherjee (1998), Ruggiero and Bretschneider (1998), Mancebón and Bandrés (1999), Ruggiero and Vitaliano (1999), Thanassoulis (1999), McEwan and Carnoy (2000), Bradley *et al.* (2001) (2010), Chakraborty *et al.* (2001), Daneshvary and Clauretie (2001), Grosskopf and Moutray (2001), Portela and Thanassoulis (2001), Fukuyama and Weber (2002), Mizala *et al.* (2002), Muñiz (2002), Thanassoulis and Portela (2002), Dolton *et al.* (2003), Hanushek and Luque (2003).

Table 2.6. Overview of outputs (cont)

1. Student achievement	
Students' test scores in different subjects (Reading, Languages, Math, Arts) / Students' performance	Wang (2003), Kiong *et al.* (2005), Oliveira and Santos (2005), Afonso and Aubyn (2006), Bougnol and Dulá (2006), Primont and Domazlicky (2006), Giménez *et al.* (2007), Waldo (2007a), Conroy and Arguea (2008), Cordero-Ferrera *et al.* (2008) (2010) (2011) (2015c), Johnes *et al.* (2008), Mancebón and Muñiz (2008), Millimet and Collier (2008), Denaux (2009), Hu *et al.* (2009), Kantabutra (2009), Sarrico and Rosa (2009), Alexander *et al.* (2010), Carpenter and Noller (2010), Cherchye *et al.* (2010), Davutyan *et al.* (2010), Essid *et al.* (2010) (2013), Houck *et al.* (2010), Khalili *et al.* (2010), Naper (2010), Portela and Camanho (2010), Sarrico *et al.* (2010), Agasisti (2011a) (2013) (2014), Kuah and Wong (2011), Mongan *et al.* (2011), Perelman and Santín (2011a) (2011b), Eff *et al.* (2012), Gronberg *et al.* (2012), Haelermans and Blank (2012), Haelermans and De Witte (2012), Haelermans *et al.* (2012), Johnes *et al.* (2012), Kirjavainen (2012), Mancebón *et al.* (2012), Misra *et al.* (2012), Montoneri *et al.* (2012), Portela *et al.* (2012) (2013), Sexton *et al.* (2012), Thieme *et al.* (2012) (2013), Aristovnik (2013), Bayraktar *et al.* (2013), De Witte and Kortelainen (2013), De Witte *et al.* (2013), Deutsch *et al.* (2013), Haelermans and Ruggiero (2013), Johnes (2013), Zoghbi *et al.* (2013), Blackburn *et al.* (2014), Brennan *et al.* (2014), Crespo-Cebada *et al.* (2014), Johnson and Ruggiero (2014), Podinovski *et al.* (2014), Agasisti and Johnes (2015).
2. Publications and research activity	
Citations (impact of research)	Thursby (2000), Korhonen *et al.* (2001), Bonaccorsi *et al.* (2006), Kocher *et al.* (2006), Abramo and D'Angelo (2009), Agasisti *et al.* (2012), De Witte and Hudrlikova (2013).
Contracts, patents, prizes / technology transfer	Ying and Sung (2000), Korhonen *et al.* (2001), Izadi *et al.* (2002), Moreno and Tadepali (2002), Flegg *et al.* (2004), Bougnol and Dulá (2006), Casu and Thanassoulis (2006), Johnes (2008), Agasisti and Johnes (2009), De Witte and Rogge (2010), Kuah and Wong (2011).
Credits given by the department	Sinuany-Stern *et al.* (1994), Tauer *et al.* (2007), Kao and Hung (2008).
Doctoral dissertations	Cherchye and Vanden Abeele (2005), Emrouznejad and Thanassoulis (2005), Bougnol and Dulá (2006), Johnes (2006a), McMillan and Chan (2006), Fandel (2007), Tyagi *et al.* (2009), Agasisti *et al.* (2011), Johnes and Schwarzenberger (2011), Kuah and Wong (2011).
Other research / teaching tasks	Sarrico and Dyson (2000), Emrouznejad and Thanassoulis (2005), Koksal and Nalcaci (2006), Colin-Glass *et al.* (2009), De Witte and Rogge (2010), Dehnokhalaji *et al.* (2010), Kounetas *et al.* (2011).
Publications (papers published in international journals, books, chapters, research output)	Johnes and Johnes (1993) (1995), Sinuany-Stern *et al.* (1994), Johnes and Johnes (1995), Mar-Molinero (1996), Madden *et al.* (1997), Thursby (2000), Ying and Sung (2000), Cherchye and Vanden Abeele (2005), Stevens (2005), Bonaccorsi *et al.* (2006), Bougnol and Dulá (2006), Kocher *et al.* (2006), Koksal and Nalcaci (2006), Anderson *et al.* (2007), Tauer *et al.* (2007), Johnes and Yu (2008), Kao and Hung (2008), Worthington and Lee (2008), Abbott and Doucouliagos (2009), Abramo and D'Angelo (2009), Cokgezen (2009), Colin-Glass *et al.* (2009), Hu *et al.* (2009), De Witte and Rogge (2010), Kantabutra and Tang (2010), Rayeni and Saljooghi (2010), Agasisti *et al.* (2011) (2012), Kounetas *et al.* (2011), Kuah and Wong (2011), Lee (2011), Wolszczak-Derlacz and Parteka (2011), Bayraktar *et al.* (2013), Lu and Chen (2013), Duh *et al.* (2014), Nazarko and Saparauskas (2014).

Table 2.6. Overview of outputs (cont)

2. Publications and research activity	
Quality of teaching/ research (ranking/index/ standard)	Beasley (1990), Beasley (1995), Johnes (1996), Cengiz and Yuki (1998), Avkiran (2001), Korhonen *et al.* (2001), Flegg *et al.* (2004), Giménez and Martínez (2006), Koksal and Nalcaci (2006), Johnes *et al.* (2008), Johnes and Yu (2008), Hu *et al.* (2009), Tyagi *et al.* (2009), Dehnokhalaji *et al.* (2010), Eff *et al.* (2012), De Witte and Hudrlikova (2013), Mayston (2014).
Research grants/ Research income	Beasley (1990) (1995), Sinuany-Stern *et al.* (1994), McMillan and Datta (1998), Sarrico and Dyson (2000), Izadi *et al.* (2002), Abbott and Doucouliagos (2003), Flegg *et al.* (2004), Emrouznejad and Thanassoulis (2005), Agasisti and Dal Bianco (2006), Bougnol and Dulá (2006), Johnes (2006a) (2008) (2014), McMillan and Chan (2006), Agasisti and Salerno, (2007), Kao and Hung (2008), Ray and Jeon (2008), Worthington and Lee (2008), Agasisti and Johnes (2009) (2010) (2015), Hu *et al.* (2009), Johnes and Johnes (2009), Tyagi *et al.* (2009), Agasisti and Pérez-Esparrells (2010), Katharaki and Katharakis (2010), Kempkes and Pohl (2010), Agasisti *et al.* (2011) (2012), Lee (2011), Johnes and Schwarzenberger (2011), Thanassoulis *et al.* (2011), Duh *et al.* (2014).
3. Educational results	
Attendance rate	Bradley *et al.* (2001), Daneshvary and Clauretie (2001), Grosskopf and Moutray (2001).
Dropout rate	Ruggiero (1996a), Ruggiero and Vitaliano (1999), Alexander *et al.* (2010).
Enrollment (number of students)	McMillan and Datta (1998), Ray and Mukherjee (1998), McEwan and Carnoy (2000), Sarrico and Dyson (2000), Avkiran (2001), Daneshvary and Clauretie (2001), Moreno and Tadepali (2002), Abbott and Doucouliagos (2003), Banker *et al.* (2004), McMillan and Chan (2006), Agasisti and Salerno, (2007), Kuo and Ho (2008), Ray and Jeon (2008), Cokgezen (2009), Tyagi *et al.* (2009), Agasisti and Johnes (2010), Davutyan *et al.* (2010), Essid *et al.* (2010) (2013) (2014), Ouellette and Vierstraete (2010), Johnes and Schwarzenberger (2011), Lee (2011), Eff *et al.* (2012), Aristovnik (2013), Bayraktar *et al.* (2013), Burney *et al.* (2013), Lu and Chen (2013), Aristovnik and Obadic (2014), Brennan *et al.* (2014), Johnes (2014), Podinovski *et al.* (2014).
Meals served/beds	Essid *et al.* (2010) (2013) (2014).
Overseas staff/students	Sarrico and Dyson (2000), De Witte and Hudrlikova (2013).
Teachers' attitude	Montoneri *et al.* (2012).
Tuition revenues	Robst (2001), Casu and Thanassoulis (2006), Ray and Jeon (2008).
4. Job Market/Success	
Employability (Graduates with job, destination)	Johnes (1996), Sarrico and Dyson (2000), Avkiran (2001), Tyagi *et al.* (2009), Agasisti (2011b), Kuah and Wong (2011), Kong and Fu (2012), Aristovnik (2013), Johnes (2013).
Starting salary of graduates	Cengiz and Yuki (1998), Agasisti (2011b), Kong and Fu (2012).
Student satisfaction (questionnaires)	Colbert *et al.* (2000), Giménez and Martínez (2006), Agasisti (2011b), De Witte and Rogge (2011), Kong and Fu (2012), De Witte and Hudrlikova (2013), Johnes (2013), Mainardes *et al.* (2014).

Another set of frontier efficiency measurement studies that deserves particular attention is the literature concerned with universities and academic departments within universities. Table 2.6 indicates that their outputs are measured in categories of published work in journals or books (in 37 papers), number of citations (in 7 papers), number of research grants or incomes achieved (in 33 papers), patents, contracts and prized obtained (in 11 papers) and other measures about the quality of teaching/research (ranking or indices – 17 papers).

There are two major points with the set of used outputs. First, the level of performance (like graduation rates, passing rates or average test scores) not only is the result of current level of educational inputs, but also the inputs provided in earlier academic years. Gronberg *et al.* (2012) argue persuasively that value-added analysis (which measures changes in student performance from one year to the next) yields better output measures for efficiency analysis than those relying on levels measures of performance. In the context of DEA, Portela and Thanassoulis (2001) were the first to isolate the effects on pupil results that are due to different efforts of pupils (i.e. pupil efficiency), from the effects that are due to differences in the school attended (i.e. school efficiency).

Second, all these outputs concentrate on educational outcomes at short or middle-term. However, there is an increasing tendency to specify long-term educational benefits in more recent work (e.g. Tyagi *et al.,* 2009; Agasisti, 2011b; Kong and Fu, 2012). These studies focus on the number of graduates who achieve a job after finishing their studies or the starting salary of graduates.

2.2.3.3 Environmental variables

Non-discretionary or environmental variables heavily account for differences in academic results. One of the main (and most controversial) conclusions of the Coleman Report (1966) was that educational resources explained only 10% of academic results, while the remainder percentage depends on other economic variables and the family environment of students. The principal analytical focus in the mainstream educational efficiency literature has been to study, through different methodological approaches, the influence of structural, institutional and socio-economic variables on efficiency scores (Worthington, 2001).

As in the case of discretionary inputs one can identify different categories of non-discretionary variables at student and family level, education institution, and community level. Table 2.7 summarizes the variables that have been used in each category and the observed effect on students' results. Comparing Table 2.7 with Tables 2.2-2.5 it is apparent that many scholars considered the same variables as both input and contextual variables.

Regarding student-related variables, the literature has focused on studying the effect of questions related to race, ethnicity, minorities or nationalities on students' results (15 papers). For example, Bradley *et al.* (2010) found that the percentage of students from non-white ethnic backgrounds increase the efficiency scores. On the contrary, Crespo-Cebada *et al.* (2014) conclude that those students who were born abroad or those whose parents were born abroad (at least one of them) obtain lower results than native students. A possible explanation for this dissimilar finding refers to the fluency of non-native students with the language. It would be worth noting that non-native students may make faster educational progress once they improve their skills in the native language than do native students (Demie and Strand, 2006; Easby, 2015). Another substantial part of the literature (15 papers) has paid attention to the impact of the number of students with special educational needs on students' achievement and costs.

Regarding family variables, socio-economic status and educational level of parents (35 papers) represent key environmental variables in determining students' results. There is a global consensus about the impact of these variables as deemed predictive of educational achievement. Most of the authors conclude by saying that the higher the status or level of education from parents, the better the results obtained by the students (e.g. Cherchye *et al.,* 2010; Blackburn *et al.,* 2014). However, this relationship is not always clear (Sirin, 2005). Authors as De Witte and Kortelainen (2013) have focused on seeing if the maternal or paternal effect on the results is more important. They found that both are statistically significant.

Table 2.7. Overview of non-discretionary variables

Category	Examples	Observed effect
1. Student variables		
Disabilities (additional educational needs)	Barrow (1991), Cubbin and Zamani (1996), Duncombe *et al.* (1997), Mancebón and Mar-Molinero (2000), Chakraborty *et al.* (2001), Abbott and Doucouliagos (2002), Rassouli-Currier (2007), Bradley *et al.* (2010), Carpenter and Noller (2010), Houck *et al.* (2010), Naper (2010), Gronberg *et al.* (2012), Johnes *et al.* (2012), Grosskopf *et al.* (2014), Cordero *et al.* (2015c).	If higher, lower achievement (and higher costs)
Free lunch/pay full lunch	Barrow (1991), Thanassoulis (1999), Chakraborty *et al.* (2001), Rassouli-Currier (2007), Conroy and Arguea (2008), Carpenter and Noller (2010), Misra *et al.* (2012).	Mixed results
Gender	Thanassoulis (1999), Millimet and Collier (2008), Bradley *et al.* (2010), De Witte and Rogge (2010), Wolszczak-Derlacz and Parteka (2011), Johnes *et al.* (2012), Deutsch *et al.* (2013).	Mixed results
Grants	Ray (1991), Conroy and Arguea (2008), Lee (2011).	Mixed results
Language background (limited English)	Duncombe *et al.* (1997), Ruggiero (1999), Primont and Domazlicky (2006), Millimet and Collier (2008), Cherchye *et al.* (2010), Gronberg *et al.* (2012), De Witte and Kortelainen (2013), Grosskopf *et al.* (2014).	If it is not English, lower students' results
Prior achievement	Bonesrønning and Rattsø (1994), Thanassoulis (1999), Cherchye *et al.* (2010), De Witte and Rogge (2010) (2011).	The higher, the better for students' results
Race/ethnicity/minority/ nationality	Ray (1991), Chalos and Cherian (1995), Chalos (1997), Ruggiero (1999), Thanassoulis (1999), Primont and Domazlicky (2006), Millimet and Collier (2008), Bradley *et al.* (2010), Carpenter and Noller (2010), Houck *et al.* (2010), Cordero-Ferrera *et al.* (2011), Johnes *et al.* (2012), Misra *et al.* (2012), De Witte and Kortelainen (2013), Crespo-Cebada *et al.* (2014).	If immigrant, lower students' results
2. Family variables		
Family structure	Mayston and Jesson (1988), Ray (1991), Duncombe *et al.* (1997), Ruggiero and Vitaliano (1999), Muñiz (2002), De Witte and Kortelainen (2013).	Mixed results
Parental education	Duncombe *et al.* (1997), Chakraborty *et al.* (2001), Muñiz (2002), Kiong *et al.* (2005), Afonso and Aubyn (2006), Millimet and Collier (2008), Cherchye *et al.* (2010), De Witte and Kortelainen (2013), Deutsch *et al.* (2013), Zoghbi *et al.* (2013), Crespo-Cebada *et al.* (2014).	If lower, then lower students' results
Relationship with children / involvement at home	Mancebón and Mar-Molinero (2000), Muñiz (2002), Giménez *et al.* (2007), Cordero-Ferrera *et al.* (2008) (2010) (2015c), Agasisti (2011a) (2013), Deutsch *et al.* (2013).	If better, then higher students' results
Resources available at home / internet use	Giménez *et al.* (2007), De Witte and Kortelainen (2013), Agasisti (2014).	If lower, then lower students' results
Socio-economic status (family income, employment)	Mayston and Jesson (1988), Ray (1991), McCarty and Yaisawarng (1993), Chalos and Cherian (1995), Engert (1996), Chalos (1997), Duncombe *et al.* (1997), Ruggiero and Bretschneider (1998), Gershberg and Schuermann (2001), Muñiz (2002), Kiong *et al.* (2005), Ouellette and Vierstraete (2005), Primont and Domazlicky (2006), Giménez *et al.* (2007), Rassouli-Currier (2007), Cordero-Ferrera *et al.* (2008) (2010), Millimet and Collier (2008), Alexander *et al.* (2010), Carpenter and Noller (2010), Cherchye *et al.* (2010), Houck *et al.* (2010), Gronberg *et al.* (2012), Thieme *et al.* (2012), Deutsch *et al.* (2013), Zoghbi *et al.* (2013), Blackburn *et al.* (2014).	If lower, then lower students' results, although mixed results were found.

Table 2.7. Overview of non-discretionary variables (cont)

3. Education institution variables		
Attendance rate/drop out	Deller and Rudnicki (1993), Chalos (1997), Carpenter and Noller (2010), Zoghbi *et al.* (2013), Cordero *et al.* (2015c).	If lower, lower students' results
Hiring practices	Naper (2010).	Decentralized is better
Local/External funding (revenues for tuition fees)	McMillan and Datta (1998), Abbott and Doucouliagos (2002), Cherchye and Vanden Abeele (2005), Denaux (2009), Houck *et al.* (2010), Naper (2010), Agasisti (2011b) (2014), Wolszczak-Derlacz and Parteka (2011), De Witte and Kortelainen (2013).	If higher, better efficiency scores
Ownership (public, private, charter). Type of institution	Johnes (1996), Duncombe *et al.* (1997), Bradley *et al.* (2001) (2010), Alexander *et al.* (2010), Kempkes and Pohl (2010), Agasisti (2011a) (2011b) (2013), Cordero-Ferrera *et al.* (2011), Kounetas *et al.* (2011), Wolszczak-Derlacz and Parteka (2011), Gronberg *et al.* (2012), Haelermans and Blank (2012), Haelermans and De Witte (2012), Haelermans *et al.* (2012), De Witte and Kortelainen (2013), Deutsch *et al.* (2013), Crespo-Cebada *et al.* (2014), Duh *et al.* (2014).	Mixed results
Quality of teaching/ researching (innovation)	Mancebón and Mar-Molinero (2000), De Witte and Rogge (2011), Haelermans and Blank (2012), Haelermans and De Witte (2012).	If higher, better students' results
Rate of expulsion or suspension	Conroy and Arguea (2008), Cordero-Ferrera *et al.* (2011), Crespo-Cebada *et al.* (2014).	If higher, lower students' results
Organization/ climate/religious orientation	Mancebón and Mar-Molinero (2000), Abbott and Doucouliagos (2002), Kounetas *et al.* (2011), Gronberg *et al.* (2012), De Witte and Kortelainen (2013), De Witte *et al.* (2013), Duh *et al.* (2014), Cordero *et al.* (2015c).	Not always significant
Size (number of students/class size/students' teacher ratio)	Barrow (1991), Duncombe *et al.* (1997), McMillan and Datta (1998), Mancebón and Mar-Molinero (2000), Abbott and Doucouliagos (2002), Cherchye and Vanden Abeele (2005), Bonaccorsi *et al.* (2006), McMillan and Chan (2006), Rassouli-Currier (2007), Millimet and Collier (2008), Alexander *et al.* (2010), Bradley *et al.* (2010), Carpenter and Noller (2010), Houck *et al.* (2010), Naper (2010), Agasisti (2011a) (2011b) (2013), Cordero-Ferrera *et al.* (2011), De Witte and Rogge (2011), Gronberg *et al.* (2012), Haelermans and De Witte (2012), Haelermans *et al.* (2012), Johnes *et al.* (2012), Burney *et al.* (2013), De Witte and Hudrlikova (2013), De Witte and Kortelainen (2013), Crespo-Cebada *et al.* (2014), Duh *et al.* (2014).	Mixed results (large institutions can reduce costs, but results are worsen)
Structure (enrolment / proportion of boys and girls)	McMillan and Datta (1998), Mancebón and Mar-Molinero (2000), Bradley *et al.* (2001), Alexander *et al.* (2010), Agasisti (2011a) (2013), Johnes *et al.* (2012), Burney *et al.* (2013), De Witte and Kortelainen (2013), Zoghbi *et al.* (2013), Crespo-Cebada *et al.* (2014).	Mixed results
Teacher characteristics (age/ gender/education /experience/number/ salary)	Cubbin and Zamani (1996), Chalos (1997), Abbott and Doucouliagos (2002), Rassouli-Currier (2007), Alexander *et al.* (2010), Bradley *et al.* (2010), Carpenter and Noller (2010), De Witte and Rogge (2010) (2011), Naper (2010), Haelermans and Blank (2012), Haelermans *et al.* (2012), Johnes *et al.* (2012), Burney *et al.* (2013), Agasisti (2014).	Mixed results, not always significant

Table 2.7. Overview of non-discretionary variables (cont)

4. Community variables		
Competition (Herfindahl index/ number of faculties within X km)	McMillan and Datta (1998), McMillan and Chan (2006), Naper (2010), Agasisti (2011a), Haelermans and Blank (2012), Haelermans *et al.* (2012), Misra *et al.* (2012).	Mixed results
GDP per capita	Ray (1991), Afonso and Aubyn (2006), Kempkes and Pohl (2010), Agasisti (2011b) (2014), Wolszczak-Derlacz and Parteka (2011), Zoghbi *et al.* (2013), Cordero *et al.* (2015c).	The higher, the better
Immigrants	Gershberg and Schuermann (2001), Denaux (2009), De Witte and Kortelainen (2013), Crespo-Cebada *et al.* (2014).	The higher the proportion, the worse
Mortality/crime-violence	Cubbin and Zamani (1996), Conroy and Arguea (2008)	Mixed results.
Neighborhood characteristics (employment opportunities/ access to wealth/poverty rate)	Cubbin and Zamani (1996), Johnes (1996), Duncombe *et al.* (1997), Ruggiero and Vitaliano (1999), Bradley *et al.* (2001) (2010), Oliveira and Santos (2005), Primont and Domazlicky (2006), Anderson *et al.* (2007), Rassouli-Currier (2007), Millimet and Collier (2008), Houck *et al.* (2010), Agasisti (2011b) (2014), Haelermans and Blank (2012), Haelermans and De Witte (2012), Haelermans *et al.* (2012), Johnes *et al.* (2012), Haelermans and Ruggiero (2013), Grosskopf *et al.* (2014).	If detrimental, lower students' results If job scarcity, lower students' results
% of households with school-aged children	Ruggiero *et al.* (1995), Duncombe *et al.* (1997), Ruggiero and Vitaliano (1999).	Mixed results
% of population with /without higher education	Ray (1991), Ruggiero (1996a) (2000), Rassouli-Currier (2007), Denaux (2009), Bradley *et al.* (2010), Naper (2010), Agasisti (2011b), Johnes *et al.* (2012), Zoghbi *et al.* (2013).	The higher, the better for students' results
Population / district size	Chalos (1997), Duncombe *et al.* (1997), Bradley *et al.* (2001), Primont and Domazlicky (2006), Millimet and Collier (2008), Alexander *et al.* (2010), Agasisti (2013), Crespo-Cebada *et al.* (2014).	Mixed results
Urban/rural area (location)	Barrow (1991), Cubbin and Zamani (1996), Johnes (1996), Duncombe *et al.* (1997), Bradley *et al.* (2001), Millimet and Collier (2008), Naper (2010), Agasisti (2011a) (2013), Lee (2011), Haelermans and Blank (2012), Haelermans and De Witte (2012), Haelermans *et al.* (2012), Misra *et al.* (2012), Burney *et al.* (2013), Deutsch *et al.* (2013), Cordero *et al.* (2015c).	Urban educational institutions achieve better results and can reduce costs

With respect to education institutions variables, ownership (public, private, charter; 20 papers) provides mixed evidence on the efficiency scores. While this topic is very country-dependent, we observed some interesting findings. On the one hand, if students attend a private institution, their level of performance would tend to be higher. However, authors like Agasisti (2013) found that efficiency scores in private high schools are lower than in public institutions. This could be explained by the fact that the higher resources available in private schools are no longer translated to better students' results. On the other hand, Cordero-Ferrera *et al.* (2011) conclude that ownership is not significant. Overall, the mixed results in the literature review can be due to country specific heterogeneity, the economic situation of the family, the level of competition among schools, the class size and the admission policy, among other factors (Mancebón and Muñiz, 2008). Closely related to the type of institution is size, most frequently defined by class size, number of students, or teacher-pupil ratio (29 papers). These variables also provide mixed results. On the one hand, smaller class sizes and lower teacher-pupil ratios may have a positive effect on students' achievement due to better educational practices by teachers, or because they can be more focused on the students (e.g. in higher education De Witte and Hudrlikova, 2013). On the other hand, authors like Haelermans and De Witte (2012) or Haelermans *et al.* (2012) observe that student-teacher ratios in secondary education do not have significant influence on students' results. Lastly, community variables include neighborhood characteristics (20 papers), location (17 papers), the level of competition (7 papers), as well as proxies for various demographic variables such as mortality rate, crime and violence or immigrants.

2.2.4 Methodological approaches

Although there are many empirical approaches to measuring efficiency (see Johnes, 2015 and references therein), the efficiency in education literature has mainly used frontier methods in two forms: non-parametric (DEA, FDH, order-*m* frontiers) and parametric (SFA) methods[3] (see Table 2.8).

[3] A review of the advantages and shortcomings of different frontier analysis techniques can be found in Fried *et al.* (2008).

Table 2.8. Observed approaches, methods, and models

A. Non-parametric approaches and semi-parametric approaches
1. Data Envelopment Analysis (DEA)
1.1. DEA (Descriptive statistics, Sensitivity analysis, slacks, significance tests, etc.)
Observed in: Bessent and Bessent (1980), Charnes *et al.* (1981), Bessent *et al.* (1982), Jesson *et al.* (1987), Smith and Mayston (1987), Sengupta and Sfeir (1988), Färe *et al.* (1989), Beasley (1990), Ganley and Cubbin (1992), Kao and Yang (1992), Johnes and Johnes (1993) (1995), Bonesrønning and Rattsø (1994), Breu and Raab (1994), Sinuany-Stern *et al.* (1994), Thanassoulis and Dunstan (1994), Beasley (1995), Chalos and Cherian (1995), Ruggiero *et al.* (1995), Engert (1996), Mar-Molinero (1996), Ruggiero (1996a) (1999) (2007), Thanassoulis (1996), Athanassopoulos and Shale (1997), Chalos (1997), Madden *et al.* (1997), Cengiz and Yuki (1998), McMillan and Datta (1998), Ray and Mukherjee (1998), Mancebón and Bandrés (1999), Thanassoulis (1999), Colbert *et al.* (2000), Sarrico and Dyson (2000), Thursby (2000), Ying and Sung (2000), Avkiran (2001), Korhonen *et al.* (2001), Portela and Thanassoulis (2001), Fukuyama and Weber (2002), Moreno and Tadepali (2002), Abbott and Doucouliagos (2003), Banker *et al.* (2004), Emrouznejad and Thanassoulis (2005), Joumady and Ris (2005), Kiong *et al.* (2005), Agasisti and Dal Bianco (2006), Bougnol and Dulá (2006), Casu and Thanassoulis (2006), Kocher *et al.* (2006), Giménez and Martínez (2006), Johnes (2006c), Fandel (2007), Giménez *et al.* (2007), Tauer *et al.* (2007), Mancebón and Muñiz (2008), Ray and Jeon (2008), Abramo and D'Angelo (2009), Cokgezen (2009), Colin-Glass *et al.* (2009), Kantabutra (2009), Sarrico and Rosa (2009), Tyagi *et al.* (2009), Dehnokhalaji *et al.* (2010), Kantabutra and Tang (2010), Katharaki and Katharakis (2010), Portela and Camanho (2010), Sarrico *et al.* (2010), Eff *et al.* (2012), Portela *et al.* (2012), Agasisti *et al.* (2012), Montoneri *et al.* (2012), Sexton *et al.*(2012), Aristovnik (2013), Aristovnik and Obadic (2014), Mainardes *et al.* (2014), Mayston (2014), Nazarko and Saparauskas (2014).
1.2. DEA (Assurance region)
Observed in: Koksal and Nalcaci (2006), Kao and Hung (2008), Khalili *et al.* (2010), Kong and Fu (2012).
1.3. Directional Distance Functions (cost direct, cost indirect, input, output distance functions)
Observed in: Grosskopf *et al.* (1997) (1999), Grosskopf and Moutray (2001), Waldo (2007a), Johnes (2008), Johnes and Yu (2008), Davutyan *et al.* (2010), Haelermans *et al.* (2012), Thieme *et al.* (2012), Portela *et al.* (2013), Brennan *et al.* (2014).
1.4. DEA + Bootstrapping procedure
Observed in: Johnes (2006a), Essid *et al.* (2010) (2013).
1.5. Multi-stage DEA (OLS, Canonical, HLM, Tobit, Truncated, with or without bootstrapping)
Observed in: Mayston and Jesson (1988), Ray (1991), McCarty and Yaisawarng (1993), Ruggiero (1996b), Duncombe *et al.* (1997), Kirjavainen and Loikkanen (1998), McMillan and Datta (1998), Ruggiero and Bretschneider (1998), Mancebón and Mar-Molinero (2000), Bradley *et al.* (2001) (2010), Abbott and Doucouliagos (2002), Muñiz (2002), Cherchye and Vanden Abeele (2005), Ouellette and Vierstraete (2005), Afonso and Aubyn (2006), Primont and Domazlicky (2006), Agasisti and Salerno (2007), Anderson *et al.* (2007), Rassouli-Currier (2007), Waldo (2007b), Cordero-Ferrera *et al.* (2008) (2010), Denaux (2009), Hu *et al.* (2009), Alexander *et al.* (2010), Houck *et al.* (2010), Naper (2010), Agasisti (2011a) (2011b) (2013) (2014), Kounetas *et al.* (2011), Lee (2011), Wolszczak-Derlacz and Parteka (2011), Johnes *et al.* (2012), Mancebón *et al.* (2012), Burney *et al.* (2013), Duh *et al.* (2014).
1.6. DEA + Malmquist Index
Observed in: Flegg *et al.* (2004), Worthington and Lee (2008), Agasisti and Dal Bianco (2009), Agasisti and Johnes (2009), Agasisti and Pérez-Esparrells (2010), Bradley *et al.* (2010), Ouellette and Vierstraete (2010), Rayeni and Saljooghi (2010), Agasisti *et al.* (2011), Thanassoulis *et al.* (2011), Agasisti (2014), Essid *et al.* (2014), Johnson and Ruggiero (2014).

Table 2.8. Observed approaches, methods, and models (cont)

2. Free Disposal Hull (FDH), Order-*m*, conditional efficiency (DEA, FDH, BoD, Order-*m*)
Observed in: Oliveira and Santos (2005), Bonaccorsi *et al.* (2006), Cherchye *et al.* (2010), De Witte *et al.* (2010) (2013), De Witte and Rogge (2010) (2011), Haelermans and De Witte (2012), De Witte and Hudrlikova (2013), De Witte and Kortelainen (2013), Haelermans and Ruggiero (2013), Thieme *et al.* (2013), Blackburn *et al.* (2014), Cordero *et al.* (2015c).
3. Metafrontier
Observed in: Ruggiero (2000), Thanassoulis and Portela (2002), Lu and Chen (2013), Thieme *et al.* (2013), Cordero *et al.* (2015c).
4. Other approaches (joint production, network, nested, hybrid returns to scale, simulation)
Observed in: Wang (2003), Johnes (2006a), Rayeni and Saljooghi (2010), Kuah and Wong (2011), Johnes (2013), Podinovski *et al.* (2014), Cordero *et al.* (2015b).
B. Parametric approaches
1. Stochastic Frontier Analysis (SFA)
1.1. SFA (Translog or Cobb-Douglas function, C-OLS, Stochastic Distance Functions, Stochastic Cost frontier)
Observed in: Butler and Monk (1985), Sengupta and Sfeir (1986), Deller and Rudnicki (1993), Jimenez and Paqueo (1996), Cooper and Cohn (1997), Heshmati and Kumbhakar (1997), McEwan and Carnoy (2000), Daneshvary and Clauretie (2001), Gershberg and Schuermann (2001), Grosskopf *et al* (2001), Izadi *et al.* (2002), Dolton *et al.* (2003), Hanushek and Luque (2003), Stevens (2005), Conroy and Arguea (2008), Johnes *et al.* (2008), Kuo and Ho (2008), Millimet and Collier (2008), Abbott and Doucouliagos (2009), Grosskopf *et al.* (2009), Carpenter and Noller (2010), Houck *et al.* (2010), Cordero-Ferrera *et al.* (2011), Mongan *et al.* (2011), Perelman and Santín (2011a) (2011b), Gronberg *et al.* (2012), Haelermans and Blank (2012), Kirjavainen (2012), Misra *et al.* (2012), Deutsch *et al.* (2013), Zoghbi *et al.* (2013), Crespo-Cebada *et al.* (2014), Mayston (2014).
1.2. Random Parameters Stochastic Frontier Model
Observed in: Johnes and Johnes (2009), Agasisti and Johnes (2010) (2015), Johnes and Schwarzenberger (2011).
C. Mixed approaches (DEA + SFA, DEA+MLM, performance indicators)
Observed in: Sengupta (1987), Taylor and Johnes (1989), Diamond and Medewitz (1990), Barrow (1991), Cubbin and Zamani (1996), Johnes (1996) (2006b), Bates (1997), Ruggiero and Vitaliano (1999), Chakraborty *et al.* (2001), Robst (2001), Mizala *et al.* (2002), McMillan and Chan (2006), Kempkes and Pohl (2010), Bayraktar *et al.* (2013), Grosskopf *et al.* (2014), Johnes (2014).

Frontier models have attracted significant attention of researchers. The reason is that the frontier concept faithfully illustrates the essential characteristics of measuring efficiency as it tries to assess how well an organization is achieving maximum output with minimum consumption of inputs. Despite being widely used there are advantages and disadvantages to each approach. First, non-parametric methods can handle multiple inputs and outputs in a simple manner, while most stochastic approaches require choosing a single explicative variable.

Second, non-parametric approaches do not require any assumptions about the functional form or specification of the error term, while stochastic methods need these assumptions. In addition, non-parametric approaches assume that all deviations from the frontier are due to inefficiency. This means that bounds on estimates cannot easily be determined, and statistical significance is not available in the traditional models.

As can be seen from Table 2.8, education has been a popular area of application of DEA (in its different variants) and it is one of the top five areas of application of this methodological approach (Liu *et al.,* 2013). Another body of the literature has focused on the use of parametric methods such as SFA (introduced by Aigner *et al.* 1977; Battese and Corra, 1977; and Meeusen and van den Broeck, 1977).

At this point, some particularly novel applications of frontier methods might be noted. These approaches have been proposed to deal with two issues that arise in this context. The first one is related to the problem of unobserved heterogeneity and the second one with the inclusion of environmental variables in the efficiency model. On the one hand, an inappropriate treatment of unobserved heterogeneity will distort estimates of inefficiency. Unobserved heterogeneity is related to environmental factors that are unobserved but constant for each unit (Greene, 2005). Research on efficiency has addressed this problem by using different approaches, such as the random parameters SFA (Tsionas, 2002). Unobserved heterogeneity enters into the stochastic frontier model in the form of ''effects'' and is usually viewed as an issue of panel data. As can be seen from Table 2.8, some empirical studies on efficiency in education have used this method (e.g., Johnes and Johnes, 2009; Agasisti and Johnes, 2010, 2015; and Johnes and Schwarzenberger, 2011).

On the other hand, the literature provides several methodologies to incorporate environmental variables in the efficiency estimation. However, there is no consensus among researchers about which of the various methodological alternatives is the most appropriate. We do not aim to provide an answer to this intricate question, but rather summarize the earlier literature applying the methodologies. The so-called two-step method is popular and widely employed. In this approach the first stage includes only discretionary inputs, and in a second stage the non-discretionary variables are regressed on the efficiency scores from the first stage. A drawback of this method is that not all important variables are necessarily identified and used in the regression. Simar and Wilson (2007) have recommended that if this approach is taken, truncated rather than Tobit regression is appropriate and a bootstrap of those results should be included to address serial correlation issues. Daraio and Simar (2005) suggest using robust conditional estimators (such as order-*m* frontiers and alpha-quantile approaches) to introduce and analyze the effects of environmental variables. This type of approach has been employed by Haelermans and De Witte (2012), Thieme *et al.* (2012), among others. More recently, Badin *et al.* (2012) have proposed a two-stage procedure in the context of robust, conditional estimators with second stage non-parametric regression (e.g. De Witte and Kortelainen, 2013).

Lastly, some papers have applied a dynamic approach such as Malmquist index (introduced as a theoretical index by Caves *et al.,* 1982) in order to expand the findings obtained through DEA and to reveal the different changes in efficiency scores over the time (technical efficiency, scale efficiency and technological change) (e.g., Essid *et al.,* 2014; Johnson and Ruggiero, 2014). This method is particularly attractive for the education sector where multiple inputs and outputs are used and prices are unknown or difficult to estimate.

2.3 Conclusions and discussion

This chapter has systematically reviewed the extensive literature on efficiency in education. The review summarized the input, output and contextual variables used in the literature, as well as the methodologies applied. As efficiency models heavily depend on the selection of the inputs and outputs, this chapter can therefore be of use to anyone working in the field of efficiency analysis.

The literature review leads us to four main conclusions. First, it is necessary to properly quantify the influence of environmental variables on student outcomes. This process will reveal the underlying mechanisms driving the efficiency estimates, and make them more accurate. Recent models such as the conditional efficiency model are suitable for this purpose; however, with the current technologies they are inappropriate for very large datasets due to the execution time required. Second, more research is necessary on the differences among countries in educational outcomes and education system characteristics. We should be able to explain why some education systems are attaining higher education outcomes than others. The availability of international databases such as PISA and TIMSS allow researchers to conduct this research. Third, the literature review clearly reveals that researchers have to work with fairly poor proxies to measure students' abilities, education institution financing, or information and communication technology (ICT) investments. We should invest more in better and more detailed data on human resources, finance, ICT, procurement, and student services. The variables used today are too generic and unspecific. We need, for example, to develop indicators that can capture teacher quality, as this may serve as a better proxy for school inputs than the commonly used school resources. Moreover, we need better output indicators to capture long-term educational benefits. Finally, more research about student added value is needed. It would be interesting to investigate students' evolution in educational terms, whether the entry educational level has remained steady, improved, or worsened within a particular educational period.

Using these insights from the literature review, we can propose practical directions for prospective researchers in the field. Apart from the above-mentioned suggestions, the efficiency literature makes a significant effort to optimize its own models. In doing so, it focusses on minor methodological details and neglects the current important issues in related fields, such as the economics of education literature. The efficiency in education literature is currently distinct from the more standard economics of education literature. To start with, they seem to have different research questions. While the economics of education literature studies the determinants of organizations' results (achievement) and/or the effects of specific policies and interventions, the efficiency literature describes the ability to transform inputs into outputs, and eventually tries to find a correlation between efficiency and organizations' characteristics or environment. Second, while the former is concerned with endogeneity issues arising from measurement errors, selection bias or unobserved heterogeneity, these issues are barely mentioned in efficiency papers. This leads us to propose practical directions for prospective researchers in both fields. By paying attention to the differences, both literatures might benefit from each other. For instance, one very fruitful focus would be to further explore the issue of causality, and how endogeneity biases the efficiency outcomes.

We acknowledge that this literature review is not without limitations, which in turn open up interesting avenues of research for the future. With regard to the methodology applied to conduct the review, a meta-analysis perspective could be usefully adopted as in the study by Rodríguez-Bolívar *et al.* (2013) for the case of financial transparency in municipalities.

Based on this literature review, the next step in the thesis is to develop the empirical analysis. To do this, in order to answer the specific objectives detailed in Section 1.2, and depending on the information provided in the database, we first use the variables adopted in previous studies. Second, based on the methodological approaches reviewed in this chapter, the thesis developed four approaches from the literature that have been used less or that are more innovative. In particular, Chapter 3 begins by applying a specific case of DEA, namely, the CDEA. As noted above, this technique has received less attention in the literature on efficiency in education; it is perfectly suitable for the first specific objective of the thesis, and it helps idenfity improvements in the management of the public education network in Catalonia, given the current economic and financial situation.

Chapter 4 applies a robust conditional order-*m* model to estimate the role of external factors in students' and schools' academic performance. As revealed in this chapter, it is necessary to properly quantify the influence of environmental variables on student outcomes. This process will reveal the underlying mechanisms driving the efficiency estimates and make them more accurate. Recent models such as the conditional efficiency model are suitable for this purpose.

Chapter 5 pursues an ambitious and completely new goal in the area of efficiency in education. We apply spatial econometric techniques together with a model of conditional efficiency to estimate the effect of location and competition on the demand for places in a school. This study will reveal the effect of competition not only on schools' performance, but also on parents' perceptions. In turn, it is a source of valid information for administrative purposes and public policy as it helps promote educational improvement programs in schools with a low demand from parents.

Finally, to respond to the fifth specific objective of this thesis and, given the need to combine the two lines of research—efficiency in education and economics of education—Chapter 6 assesses effectiveness and efficiency in the application of a quality improvement program in public schools in Catalonia. To do this, the DiD approach with panel data is first applied to estimate the impact of the program on several academic results; a longitudinal analysis of efficiency is then used, through the Malmquist index, to estimate the TFPC due to the application of the program. The conclusions of this study are quite revealing for the educational administration of Catalonia since they include insights on whether or not schools participating in the program achieved the objectives (effectiveness) and whether or not they succeeded in making the best use of available resources (efficiency).

CHAPTER 3.

CENTRALIZED ALLOCATION OF HUMAN RESOURCES. AN APPLICATION TO PUBLIC SCHOOLS

3. CENTRALIZED ALLOCATION OF HUMAN RESOURCES. AN APPLICATION TO PUBLIC SCHOOLS

3.1 Introduction

After reviewing the literature, and in view of the economic scenario in Catalonia described in Chapter 1, the second objective of this thesis is to conduct a centralized efficiency assessment of public schools in order to propose a new design in the current education network to be more efficient and competitive. To achieve this objective, we use the CDEA to establish the level of overall efficiency of the public education network and to propose improvements to those schools that have a lower performance. In addition, this chapter also ranks schools by level of technical efficiency and proposes a redistribution of scarce resources, so that it is possible to globally optimize the network performance without jeopardizing the current level of quality and academic attainment.

In recent decades, interest in efficiency in education has increased from both practitioner and academic points of view (Goldstein and Woodhouse, 2000). One of the reasons for the emergence of studies in this field is the increasing importance of the education sector in the economy since it provides intellectual training for the population, better human capital, and increased labor productivity (Blau, 1996). In addition, education is considered essential to enhance a country's economic growth (Krueger and Lindahl, 2001). In the wake of the global economic crisis, countries face the challenges of making public finances sustainable. Publicly funded sectors are under pressure to deliver more for less and none more so than the education sector. This environment requires an education system that is efficient in translating resources into educational outcomes (Johnes, 2014). In Spain, the economic reality is currently undergoing social and political debate. In the public sector, the pressure to increase performance implies that any action to improve efficiency becomes an economic policy priority. Under the current budget constraints the continuity of any public entity is a decision variable (Bel *et al.,* 2010).

Performance measurement is important not only in the private sector, but also in the public sector since it can highlight strengths and weaknesses in current practices, reveal directions for improvement, and ultimately may lead to better use of the resources spent on providing public services (Asmild *et al.,* 2012). As we detailed in Section 1.1, in the Spanish case the government rationalized education spending through an 11% budget cut to save more than 4,000 million euros by implementing certain measures at the regional level, such as increasing the student-teacher ratio, expanding the range of increases in university fees, delaying teacher replacements and even forcing the closure of several schools. For instance, in Catalonia more than seven schools have been closed in recent academic years and the regional government is planning to eliminate several elementary education groups due to lack of resources. In this environment, schools are forced to make savings in personnel budgets to keep expenditure low. These budgetary restrictions have provoked growing interest in rationalizing the allocation of available resources (Villarreal, 2002).

In spite of these global budget cutbacks, the current education system does not encourage schools to work effectively. For this to occur, reorganization is needed that will motivate education institutions to achieve good results efficiently. In the scenario of cutbacks and closures, it appears that one suggestion for increasing efficiency is to merge education institutions (Griffiths, 2010; Johnes, 2014). From a theoretical perspective, a merger may accrue efficiency benefits from returns to scale, as a consequence of increased administrative, economic and academic efficiency, or returns to scope if the merging institutions have complementary activities (Skodvin, 1999; Harman, 2000; Gordon and Knight, 2009). Previous quantitative studies on the empirical effect of merging on efficiency demonstrate that the impact on efficiency is positive (Hu and Liang, 2008; Mao *et al.,* 2009; Johnes, 2014).

Consequently, the approach proposed in this chapter consists of creating an internal performance-based scheme that stimulates an effective level of performance in public schools while complying with the budget constraints imposed by the government without losing quality. The introduction of incentives can help schools to be more efficient and sustain efficiencies over time (Burgess and Ratto, 2003; Heinrich and Marschke, 2010). The main purpose of this chapter is to propose a method to assess and re-design a group of schools in a public education network to make additional savings in the education budget. We also aim to reallocate resources through a new composition of the education network to optimize overall efficiency without jeopardizing the level of educational quality.

To develop the approach we extend a specific non-parametric frontier technique known as CDEA, initially proposed by Lozano and Villa (2004) and modified by Mar-Molinero *et al.* (2014). We extend the CDEA model in several ways. First, we include a specific constraint to deal with the inclusion of non-discretionary factors (environmental variables) in a centralized scenario. We need to bear in mind that the performance of public schools can also be affected by exogenous or environmental factors, which in the context of our study are represented mainly by the characteristics of the students, families and the nearest school environment (Muñiz, 2002). As these variables are not under the control of either the DMUs (in our case schools) or the decision maker (i.e., the Department of Education), we need to include them in our efficiency analysis in a different way.

Second, we incorporate additional constraints referring to transferable and non-transferable inputs. To do so, we design an efficiency model that encourages good educational practices and penalizes unsatisfactory results. Following Yu *et al.* (2013) the actions to improve results are determined by three main policies that regulate government powers. The first is a short-term policy under which the decision maker cannot dismiss any teachers (permanent or non-permanent) but can transfer non-permanent teachers from one school to another, while maintaining the status of permanent teachers, and the original number of schools. Secondly, the middle-term policy grants the government restricted power to dismiss only non-permanent teachers, but it can transfer permanent teachers between schools and change the original number of them. This is the alternative we propose in this chapter. Thirdly, the long-term policy refers to the possibility of dismissing any permanent or non-permanent teacher from any school. This most extreme policy is not taken into account in this chapter.

After designing the extended CDEA, we propose an iterative method capable of re-designing the public education network by reallocating resources among schools with reception capacity, taking into account environmental conditions. To that end, we apply a conditional non-parametric efficiency approach to better know which schools were the worst performers (i.e., the candidates to be merged). The conditional model is known to be a better approach than traditional models, such as two-stage models, to account for environmental factors (see Simar and Wilson, 2007; and Cordero-Ferrera *et al.,* 2008 for an overview). The validity of these traditional models is limited because they assume the separability condition between the input-output space and the space of environmental factors. Therefore, we use the so-called conditional non-parametric approach (Cazals *et al.,* 2002; Daraio and Simar, 2005, 2007a, 2007b) which avoids this restrictive separability assumption.

Previous studies on resource allocation in schools have rarely considered the issue of centralized human resource adjustment scenarios (e.g., Rubenstein *et al.,* 2007; Haelermans *et al.,* 2012; Mar-Molinero *et al.,* 2014; Grosskopf *et al.,* 2013). In addition, prior empirical papers have revealed a significant and positive relationship between human resources practices and performance (e.g., Huselid 1995; Chen and Huang 2009; Yu *et al.,* 2013). According to Chen and Huang (2009), the appropriate allocation of human resources has a positive effect on organizational performance. Yu *et al.* (2013) also argue that periodic organizational change is necessary to improve organizational performance. A new model is therefore needed to resize the education network in order to provide objective solutions to the general cutbacks proposed by the government (which affect all schools regardless their performance). In other words, it is essential to create a computational model capable of determining the poorly performing schools overall, and to design a mechanism to resizing the network without penalizing the best performers.

The results show that overall efficiency can be improved without losing outputs and quality, but this improvement depends on the objectives of the Department of Education. First, 12.7% of resources can be saved without changing the current network. Second, it would be possible to save 17.2% of resources if the network composition was changed by resizing the number of schools operating.

Our work supplements previous research in several ways. First, the extended CDEA we propose overcomes the problem of including non-transferable inputs and non-discretionary factors that were not included in previous research. Second, our analysis may be particularly relevant from a policy perspective because it establishes the actions needed to optimize the network through budget reallocation in a real case study. Third, the implementation of the proposed model in a real application provides valuable information for public authorities and facilitates the implementation of improvement programs in schools, which contributes to higher levels of quality, motivation, and fairness within the system.

Following this introduction, this chapter is structured as follows. Section 3.2 reviews the related literature on the CDEA model for resource allocation. Section 3.3 explains the methodology. Then, Section 3.4 details the data and variables we use. Subsequently, Section 3.5 summarizes and discusses the results, and finally, Section 3.6 concludes.

3.2 Empirical evidence on efficiency and resource allocation

Schools are multidimensional in nature, consisting of different functions that are difficult to quantify. The education sector is non-for-profit, there is an absence of output and input prices; and schools produce multiple outputs from multiple inputs. It is therefore a complex task to define and estimate the production technology that students use to acquire knowledge (Worthington 2001).

Several methodological approaches have been employed to solve the problem of efficiency measurement in the education context (see the literature review from Chapter 2 and Johnes, 2004; 2015, and references therein). However, the efficiency in education literature has mainly used frontier methods in two variants: non-parametric models (such as DEA (Charnes *et al.,* 1978), FDH (Deprins *et al.,* 1984), order-*m* frontiers (Cazals *et al.,* 2002)) and parametric models like SFA (Aigner *et al.,* 1977). A review of the advantages and shortcomings of different frontier analysis techniques can be found in Fried *et al.* (2008).

In this environment, DEA has become very popular in empirical studies on the economics of education, since it can easily handle multiple dimensions of performance and is less vulnerable to the misspecification problems that can affect econometric models (Worthington, 2001; Liu *et al.,* 2013). This method can also handle multiple inputs and outputs without requiring the specification of an ungranted functional form of the input-output relationship (Sinuany-Stern *et al.,* 1994). Hence, DEA is presented as a method of competitive benchmarking in terms of learning from the best practice and searching for weaknesses in an effort to increase efficiency of business processes in the future (Lozano and Villa, 2006).

Since DEA first emerged, its applications to the field of efficiency in education have grown steadily (Emrouznejad *et al.,* 2008). This line of research is based on empirical studies designed to estimate the magnitude of the impact of schools' results promoted by internal inputs and environmental factors. Since its inception, findings from this research stream have contributed to improve the knowledge and understanding of which educational elements affect students' development, thus providing information for decision making in the classroom, the school, and the education system.

Although there are numerous applications of DEA to measure school efficiency, most approaches have considered the DMUs separately, providing a relative efficiency index for each unit as compared to the rest. However, relatively few studies have applied an approach in which units are studied jointly and simultaneously projected to the efficiency frontier with an overall objective. There are situations in which the DMUs operate under a common centralized direction. This type of scenario is common when all units belong to the same organization that provides the resources needed to achieve results, such as bank branches, hospitals, public schools, supermarket chains or police stations (Mar-Molinero *et al.* 2014).

As a response to these situations, Lozano and Villa (2004) proposed the CDEA model. These authors present different centralized resource allocation models in a decision-making environment. The idea behind this formulation is to globally reduce the total use of inputs or globally increase the productions of all outputs, as opposed to the philosophy of traditional DEA models, which optimize the functioning of each DMU separately (Asmild *et al.,* 2009).

Many DEA applications can be found in this centralized scenario, although not all of them use the CDEA perspective: supermarket branches (Korhonen and Syrjänen, 2004; Wu and An, 2012; Fang 2013), hospitals (Li and Ng, 1995), universities or schools (Rubenstein *et al.,* 2007; Hadi-Vencheh *et al.,* 2008; Haelermans *et al.,* 2012; Mar-Molinero *et al.,* 2014; Grosskopf *et al.,* 2013), police stations (Asmild *et al.,* 2012), airports (Yu *et al.,* 2013), public entities (Athanassopoulos, 1995; Lozano *et al.,* 2004; Fang and Zhang, 2008; Asmild *et al.,* 2009; Lozano *et al.,* 2009; 2011) or branches of private companies (Färe *et al.,* 1997; Giménez-García *et al.,* 2007; Du *et al.,* 2010; Varmaz *et al.,* 2013). Other examples with simulated data include Lozano and Villa (2005); Nesterenko and Zelenyuk (2007) and Li and Cui (2008). In all these examples, the central authority, as well as being interested in the efficiency of each unit, is also concerned about the total consumption of inputs by different DMUs and the overall production of outputs.

Some extensions of CDEA models have appeared since Lozano and Villa (2004). For instance, Asmild *et al.* (2009) reconsider one of the centralized models proposed by Lozano and Villa (2004) (2005) and suggest modifying it to only consider adjustments of previously inefficient units. Asmild *et al.* (2012) propose a novel way to reallocate personnel resources between tasks within a specific unit as well as between similar units using a CDEA model. They show reallocations in six different scenarios to offer solutions depending on different circumstances or policy objectives that may exist in the organizations. Fang (2013) introduces a new generalized centralized resource allocation model which extends Lozano and Villa's and Asmild *et al.*'s models to a more general case. In addition, the paper considers situations in which some DMUs are geographically dispersed or for which it may be impossible to reallocate inputs or transfer outputs across DMUs because of regulation or indivisibilities. Consequently, inputs may be reallocated or outputs may be transferred, but only across some DMUs. Yu *et al.* (2013) present an alternative approach to reallocating human resources by constructing a modified CDEA model combined with a Russell measure and applied to three different human resource reallocation policies in Taiwanese airports. Finally, Mar-Molinero *et al.* (2014) developed a simplified version of the model by Lozano and Villa (2004, 2005) that makes the model easier to implement in several situations. These authors also consider the scenario in which some units could disappear because the reallocation of inputs to other units could improve the overall efficiency of the group.

In this chapter we propose a further extension of CDEA developed by Mar-Molinero *et al.* (2014) that includes transferable and non-transferable inputs and takes into account the role of environmental factors. To the best of our knowledge this new combined approach has not been considered in previous work on efficiency in education.

3.3 Methodology

3.3.1 The extended CDEA model

In this section we detail the methodology followed to achieve our main goal. We assume that all of schools are operating under the control of a decision maker represented by the Department of Education in Catalonia.

Following the education policies detailed in Section 3.1, our CDEA model can have different orientations. We run the first two policies, namely short- and middle-term policies since the long-term policy is consider too extreme for our scenario. Thus, we assume the decision maker cannot dismiss permanent teachers in any case, but can transfer them under the middle-term policy. Therefore, following Fang (2013), permanent teachers are treated differently in the restrictions of CDEA model. Another difference between short-term and middle-term policies is the treatment of non-permanent teachers, who can be transferred in both policies and made redundant only under the middle-term policy. In this case, following Mar-Molinero *et al.*'s model, we will know the number of non-permanent teachers who are candidates for dismissal.

Another improvement in our model concerns the treatment of non-discretionary factors in CDEA models. According to Asmild *et al.* (2009) and Fang (2013), when considering organizations that operate under a multi-level management hierarchy, it is important to understand that certain factors are outside the control of the local DMUs. Previous research in education has considered this situation, typically by designating these factors as non-discretionary (e.g., Muñiz, 2002; Cordero-Ferrera *et al.,* 2008; 2009; 2010; De Witte and Kortelainen, 2013). The treatment of non-discretionary factors in these examples is appropriate; however, prior literature has not taken into account the existence of non-controllable factors in a centralized model. In many cases such factors are in fact exogenously determined and beyond the control of both local and central management. Therefore, it is relevant to consider them within the analysis in order to allocate transferable resources to similar environmental conditions.

Certain assumptions need to be clarified before going any further. First, due to the different nature of the contracts, non-permanent teachers cannot replace permanent teachers and vice versa. Second, we assume there is no cost in transferring permanent teachers and/or dismissing non-permanent teachers[4]. Finally, we consider data for only one academic year, which precludes any knowledge of how the simulation of the reallocation process might affect the efficiency of schools after this procedure. However, as we stated in the introduction of this chapter, previous empirical studies have proved that mergers have a positive impact on efficiency (e.g., Skodvin, 1999; Harman, 2000; Hu and Liang, 2008; Mao *et al.,* 2009; Gordon and Knight, 2009; Johnes, 2014). For instance, Gordon and Knight (2009) apply a merger estimator to explain political integration in a wave of school district mergers in the state of Iowa during the 1990s. The authors conclude highlighting the importance of state financial incentives for consolidation (mergers) and the benefits in terms of economies of scale. In addition, Johnes (2014) deals with the effects on efficiency of merged universities in the UK. She states that merger activity in English higher education institutions seems not to be a reaction to a crisis in efficiency in the merging institutions. Specifically, a merged higher education institution is significantly more efficient than either pre-merger or non-merging institutions, suggesting that, on average, merging is a positive activity. This evidence leads us to suspect that whether or not the government undertakes these mergers, the overall efficiency of the network will be reinforced.

That said the process is developed in several stages. First, we obtain the overall efficiency of the current education network under the short-term policy (the

[4] We are aware this assumption is severe; nevertheless, it is justified because it is contemplated in the Spanish law. On the one hand, non-permanent teachers have temporary contracts that expire at the end of each academic year. Therefore, if the mergers are carried out, the education system can adjust the number of temporary contracts depending need. On the other hand, under special circumstances, the Spanish law allows permanent teachers to be reallocated among different schools without any economic incentive. In addition, similar assumptions have been made in previous papers dealing with resource allocation (e.g., Yu *et al.,* 2013).

government cannot dismiss any teachers, but can transfer non-permanent teachers). Second, we test the possibility of optimizing the performance of the network. To do this, we apply the middle-term policy and we find the optimum number of schools that the network should have to increase the overall efficiency ($n \neq n^*$). This step not only shows the optimal size of the network, but also reveals the number of schools that are candidates to be merged with other schools with reception capacity located in a similar area.

Having explained the intuition of our CDEA model, let us define j = 1, 2, ..., J: sub-index for each DMU; i = 1, 2, ..., I: sub-index for each input; k = 1, 2, ..., K: sub-index for each output; x_{ij} = amount of input i consumed by DMUj; y_{kj} = amount of output produced by the DMUj; θ = technical efficiency ratio; ($\lambda_1, \lambda_2, ..., \lambda_n$) = intensity vector of the inputs and outputs of each DMUj; t symbolizes the transferable inputs (t = 1, ..., T); while nt shows the non-transferable inputs (nt = 1, ..., NT). Lastly, z_e represents the non-discretionary or environmental factors (e = 1, ..., E). Assuming that all DMUs are under the control of the decision maker that aims to minimize the total input consumption, the input-oriented CDEA model[5] for the short-term policy can be written as follows (extension proposed following Fang (2013) and Mar-Molinero *et al.* (2014)):

$$
\begin{aligned}
& min\,\theta \\
& s.t.: \\
& \sum_{j=1}^{J} \lambda_j x_{tj} \leq \theta \sum_{j=1}^{J} x_{tj}, \quad \forall t = 1, \dots, T, \\
& \sum_{j=1}^{J} \lambda_j x_{ntj} \leq \sum_{j=1}^{J} x_{ntj}, \quad \forall nt = 1, \dots, NT, \\
& \sum_{j=1}^{J} \lambda_j z_{ej} \leq \sum_{j=1}^{J} z_{ej}, \qquad \forall e = 1, \dots, E, \\
& \sum_{j=1}^{J} \lambda_j y_{kj} \leq \sum_{j=1}^{J} y_j, \qquad \forall k = 1, \dots, K, \\
& \sum_{j=1}^{J} \lambda_j = 1, \\
& \lambda_j \geq 0, \qquad \theta\ free
\end{aligned}
\tag{3.1}
$$

[5] We focus on input orientation due to the current environment of budget constraints in the Spanish public education system. The goal is to maintain the level of educational outputs minimizing the input consumption.

where the number of schools operating in the network remains unchanged ($\sum_{j=1}^{J} \lambda_j = 1$) and any teacher can be dismissed. Transferable inputs refer to non-permanent teachers and non-transferable input to those who have permanent contracts. Non-discretionary factors are detailed in Section 3.4.2.

The CDEA model for the middle-term policy is exactly the same, but leaving free the restriction of the *lambdas* and omitting the restriction of non-transferable inputs as both categories of teachers are adjustable. The value of n^* from Eq. (3.2) indicates the optimum number of schools that the network should have to be more efficient ($n \neq n^*$). This implies that the decision maker seeks to reduce both the total number of non-permanent staff to be dismissed and those permanent teachers that can be transferred.

$$
\begin{aligned}
& \min \theta \\
& s.t.: \\
& \sum_{j=1}^{J} \lambda_j x_{tj} \leq \theta \sum_{j=1}^{J} x_{tj}, \quad \forall t = 1, \dots, T, \\
& \sum_{j=1}^{J} \lambda_j z_{ej} \leq \sum_{j=1}^{J} z_{ej}, \quad \forall e = 1, \dots, E, \\
& \sum_{j=1}^{J} \lambda_j y_{kj} \leq \sum_{j=1}^{J} y_j, \quad \forall k = 1, \dots, K, \\
& \sum_{j=1}^{J} \lambda_j = n^*, \\
& \lambda_j \geq 0, \quad \theta \; free
\end{aligned}
\tag{3.2}
$$

Once obtained this n^* ($n^* < n$) we can decide how to reallocate resources among the number of schools that make up the new education network.

3.3.2 Looking for poor-performing schools to reallocate resources

Once we have applied the CDEA model from Eq. (3.2) we will know the optimum size of the education network in order for it to be more efficient and comply with the budget constraints imposed by the government. Regarding the objective of the government, poorest performing schools can be merged with neighboring schools with available capacity. The model from Eq. (3.2) sets the optimal size of the network and the number of schools that are candidates to merge, but does not reveal which these schools are. A method is needed to find out which schools should be restructured. To do this, and following the non-parametric nature of this chapter, DEA can be used since it can easily handle multiple dimensions of performance and is less vulnerable to the misspecification problems that can affect econometric models. However, this approach presents some significant drawbacks (Cordero *et al.,* 2015c): (1) statistical inference is not possible due to its deterministic nature; (2) it is very sensitive to the presence of outliers and measurement errors in data; and (3) it experiences dimensionality problems due to its slow convergence rates.

In order to overcome these problems, Cazals *et al.* (2002) and Daraio and Simar (2005, 2007a, 2007b), introduced the order-m model (see Cazals *et al.* (2002) and Badin and Daraio (2011) for a more detailed explanation of the method, including a discussion of the method's attractive statistical properties). Order-m frontier estimators are known to be more robust to outliers, extreme values or noise in the data than the full frontier estimates (DEA or FDH). In essence, this approach does not consider the full set of observations for defining the efficiency score. Instead, it repeatedly considers subsamples of m (≥1) observations randomly drawn from the sample. Robust measures are obtained by repeating this process B times (B being a large number). For each observation, the robust order-m model is then computed as the average value of the efficiency scores $(\hat{\theta}_m^1, \dots, \hat{\theta}_m^B)$ defined over the B iterations. As outlying observations do not form part of the set m in every draw, the impact of outlying observations on these order-m efficiency scores is effectively mitigated.

Jeong *et al.* (2010) state that order-m estimates have attractive properties in that they are consistent and have a fast rate of convergence. In particular, this approach is becoming more popular in the literature on efficiency in education (e.g., De Witte *et al.,* 2010; Thieme *et al.,* 2013; among others).

Continuing with the notation introduced in Section 3.3.1, students transform a set of inputs $x \in \mathbb{R}_+^i$ into heterogeneous outputs $y \in \mathbb{R}_+^k$. In this framework, the production technology is the set of all feasible input-output combinations:

$$\Psi = \{(x, y) \in R_+^{i+k} \mid x \text{ can produce } y\} \quad (3.3)$$

In this framework, an observed production unit defines an individual production possibility set (PPS) which, under the free disposability of inputs and outputs can be written as:

$$\Psi\,(x_j, y_j) = \left\{(x, y) \in \mathrm{R}_+^{i+k} \mid x_j \geq x; y \leq y_j\right\} \quad (3.4)$$

In order to estimate the relative efficiency of each school, we estimate a frontier following the ideas developed by Farrell (1957). Specifically, the measure of output-oriented[6] efficiency score for a unit operating at the level (*x,* y) is defined as (3.5):

$$\theta(x, y) = \sup\{\theta \mid (x, \theta y) \in \Psi\} \quad (3.5)$$

Here $\theta(x, y) \geq 1$ represents the proportionate increase of outputs the unit operating at level (x, y) should attain to be considered as being efficient. The efficient frontier corresponds to those points where $\theta(x, y) = 1$. As stated in Section 3.2, and given that the set Ψ cannot be directly observed, it has to be estimated from a random sample of production units denoted by $\omega = \left\{(x, y) \in R_+^{i+k} \mid \mathrm{j} = 1, \dots, \mathrm{J}\right\}$. Since the pioneering work of Farrell (1957), the literature has developed different approaches to achieve this goal. In this paper, we focus on applying an order-*m* frontier model as it is more robust to outliers, extreme values or noise in the data than the full frontier estimates (DEA or FDH). Therefore, for a given level of inputs *x* in the interior of the support of *X*, consider *m* i.i.d. random variables Y_j, $j = 1, \dots, m$, we define the set:

$$\Psi_m(x) = \left\{(x', y) \in \mathrm{R}_+^{i+k} \mid x' \leq x, i = 1, \dots, m\right\} \quad (3.6)$$

Then, the output oriented order-*m* efficiency score ($\hat{\theta}_m$) can be obtained from Eq. (3.7) as follows:

$$\hat{\theta}_m\,(x, y) = \sup \theta \mid (x, \theta y) \in \Psi_m(x) = E[max_{j=1,\dots,m}\ \{min_{k=1,\dots,K}(\frac{y_j^k}{y^k})\} \mid X \leq x] \quad (3.7)$$

This estimator compares the efficiency of a DMU with the *m* potential observations that have a production larger than or equal to *y*. As *m* increases, the expected order-*m* estimator tends toward the DEA efficiency score. For reasonable *m* values, the

[6] In that case, in contrast to what we did with CDEA, we apply an output orientation model. The reason for this change is related to the purpose of each model. In this case, the objective is to know which schools achieve the best results with the available resources to conduct the reallocation process. In other words, our goal is to know which schools obtain the best (and worst) academic results (i.e., for benchmarking purposes) in order to establish which schools are the candidates to be merged.

efficiency score will exhibit a value higher than unity, which indicates that the unit is inefficient. When $\hat{\theta}_m < 1$, the DMU under evaluation is labeled as super-efficient, since the order-m frontier exhibits lower levels of outputs than the unit under analysis (Daraio and Simar, 2007a).

3.3.3 Dealing with environmental factors

Following with our empirical analysis, we need to bear in mind that a potential source of inefficiency is the impact of exogenous or environmental factors denoted as $z \in \mathbb{R}_+^e$. An evaluation of schools' performance should explicitly include this information to ensure that the efficiency score finally assigned to the school truly reflects the portion of the production process for which the unit itself is responsible (Muñiz, 2002).

There are different ways of incorporating the effect of environmental factors into the production process to estimate efficiency scores (see Fried *et al.* (2008) for an overview). Although traditional approaches such as the two-step method (Simar and Wilson, 2007; McDonnald, 2008) are popular and widely employed, the specific literature devoted to environmental factors and their influence on efficiency has advanced significantly with the development of a more general and appealing full non-parametric conditional approach, based on the probabilistic definition of the frontier developed by Cazals *et al.* (2002) and Daraio and Simar (2005, 2007a, 2007b).

This approach has become very popular in the recent literature on efficiency measurement. Hence, it is possible to find several studies using this approach to measure the efficiency of units operating in a wide range of settings, including the education sector (e.g., Bonaccorsi *et al.,* 2006; Cherchye *et al.,* 2010; De Witte and Kortelainen, 2013; De Witte and Rogge, 2011; De Witte *et al.,* 2013; Haelermans and De Witte, 2012).

The conditional model works with probabilistic formulation and incorporates the environmental impact conditioning the production process to a given value of the non-discretionary factors ($z = Z$). It constructs a boundary representing the reference set in which each unit is compared. This method also avoids the restrictive separability assumption required by traditional approaches in order to provide meaningful results, and does not require specification of the influence of each environmental variable on the efficiency. The set defined before in Eq. (3.6) can be adapted as follows:

$$\Psi_m(x|z) = \{(x', y) \in \mathrm{R}_+^{i+k} \mid x' \leq x, z = Z, i = 1, \ldots, m\} \tag{3.8}$$

Using a probabilistic formulation, the order-m efficiency measure defined above in Eq. (3.7) has to be adapted to the condition $z = Z$ as follows:

$$\hat{\theta}_m\,(x, y|z) = \sup \theta|(x, \theta y) \in \Psi_m(x|z) = \sup\,\{\theta|\, S_Y(\theta y|x, z) > 0\} \tag{3.9}$$

where $S_Y(y|x, z) = Prob(Y \geq y|X \leq x, Z = z)$

To estimate the conditional model, smoothing techniques are needed in *z.* For this purpose, the following kernel estimator of $S_Y\ (y|x, z)$ is used:

$$\hat{S}_{Y,n}(y|x, z) = \frac{\sum_{j=1}^{n} I(x_j \leq x, y_j \geq y) K_{\hat{h}}(z, z_j)}{\sum_{j=1}^{n} I(x_j \leq x) K_{\hat{h}}(z, z_j)} \tag{3.10}$$

where $K_{\hat{h}}(\cdot)$ represents the kernel function, $I\ (\cdot)$ is an indicator function and h is an appropriate bandwidth parameter for this kernel.

As can be seen, this approach relies on the estimation of a non-parametric kernel function to select the appropriate reference partners, and a bandwidth parameter h using a method with some bandwidth choice. In our case, we use a multivariate kernel function (developed by De Witte and Kortelainen, 2013) since we have mixed data in our data set (continuous and ordinal variables). We employ the Epanechnikov kernel function $(K_{\hat{h}}(z, z_j) = h^{-1}K(\frac{z, z_j}{h}))$ for continuous variables and the Li and Racine (2007) discrete kernel function for ordered variables. To estimate the bandwidth parameters, we follow the data-driven selection approach developed by Badin *et al.* (2010)[7]. Subsequently, the conditional order-m estimator $\hat{\theta}_m(x, y|z)$ can be obtained by plugging in the new $\hat{S}_{Y,n}(y|x, z)$ in Eq. (3.9).

[7] This approach can be easily adapted to the case of mixed environmental variables. For instance, in the case of an ordered variable, we ensure that the performance of each unit is compared only to those in the same category by forcing the bandwidth to be zero for the variable in question. This choice has been applied in previous studies as Cordero *et al.* (2015a).

The relative conditional order-m efficiency index for each DMU indicates which schools are less efficient and, therefore, those that could face mergers if the reallocation process is applied.

3.4 CDEA. A case study in public schools from Catalonia

3.4.1. The case of Catalonia

The main purpose of this chapter is to propose a method to assess and re-design a group of schools in a public education network to make additional savings in the education budget. In addition, we aim to reallocate resources through a new composition of the network to optimize the overall efficiency without jeopardizing the level of educational quality. To do so, we develop the CDEA model proposed in Section 3.3.1 in a specific Spanish region, Catalonia.

Catalonia is a region located in the north-east of Spain. It is a very densely populated and highly industrialized territory, and has led the Spanish industrial sector since the nineteenth century. Its economy is the most important of the regions in Spain, generating more than 18.7% of Spanish GDP. Like the rest of regions, Catalonia has a public education system that belongs to the Spanish public education network. The case the public education system in Catalonia is especially important for this study because, despite being traditionally one of the richest regions in Spain, it is also suffering severe cuts in education, so much so that the Department of Education is closing or merging some schools. For instance, during the academic year 2012/2013 seven schools were closed and plans were made to cut 73 elementary school groups due to lack of resources. In addition, more schools could be added to the list of closures if they do not achieve a minimum of 15 registrations. This is not a new policy, however; this was the second consecutive academic year that the Department of Education had encouraged school closures. During the previous academic year six schools were forced to close and elementary education was suspended in four others.

The underlying question is how the government determined which schools should be closed or merged and why. We wonder whether or not they have followed an objective procedure to determine which schools are the most technically inefficient, or whether this process was simply a random exercise[8]. Our goal is to apply an objective procedure for measuring the overall efficiency of the education network to determine the optimal number of schools in the network for it to be more efficient without losing quality. In other words, to determine how many schools the network should have in order to comply with the cutbacks without damaging students' results. We then determine the most inefficient schools that are candidates to be merged with other nearby schools with similar socio-economic environment.

3.4.2. Data and variables

As we stated in Chapter 1, we use a specific database from the Evaluation Council of the Education System in Catalonia (*Consell Superior d'Avaluació del Sistema Educatiu de la Generalitat de Catalunya*). The sample includes 161 primary public schools for the academic year 2009-2010, representing a specific regional educational area (REA) in Catalonia, *Vallès Occidental*. Catalonia has ten REAs covering neighboring municipalities under the control of a specific team of Inspectors of Education. We selected just one area in order to simplify the simulation of human resource reallocation to neighboring schools.

The relevant unit of observation is the school. We are aware of the importance of having student level data and the problems that aggregation could cause (Hanushek *et al.,* 1996). However, we decided to maintain school level data because it contains information about the geographical location of each school. These data allow us to subsequently reallocate resources to neighboring schools[9].

To select the variables, we follow the literature about efficiency in education reviewed in Chapter 2. In general, a global consensus exists concerning the

[8] An example retrieved from the news demonstrates the weak criteria followed by the government to close some schools. For instance, a school located in the metropolitan area of Barcelona was closed because of its disreputable location, despite running an educational project that improved students' outcomes by more than 50%.
[9] The possibility of having student level data available should not mean that the implications of the study would be dramatically different from an analysis of efficiency to reallocate resources.

consideration of indicators about academic achievement as outputs. However, the selection of inputs and environmental variables can be complex and, in some cases, even confusing. Given that the literature does not specify precisely how to discriminate between them, in this thesis we have based our decision on the following criterion: input variables must fulfil the requirement of isotonicity (i.e., *ceteris paribus*, more input implies an equal or higher level of output). Thus, the selected input variable should present a significant positive correlation with the output vector in addition to having theoretical support from previous works.

As can be seen from Table 3.1, the output we use are the grades in homogeneous aptitude tests done by all students in Catalonia in the last year of primary education (e.g., Bessent and Bessent, 1980; Bessent *et al.,* 1982; Ray, 1991; Chalos and Cherian, 1995; Mancebón and Mar-Molinero, 2000; Rubenstein *et al.,* 2007). As our unit of analysis is the school, we consider the sum of the arithmetic mean of the students' grades in the sixth grade general tests conducted in Catalonia (Y_1) and the number of students who pass the exams (Y_2).

Table 3.1. Description of variables

Category	***Variable***		***Description***
Inputs	X_1	Permanent teachers	Total number of teachers with a stable contract.
	X_2	Non-permanent teachers	Total number of temporary teachers.
	X_3	OPEX	Operational expenses in the academic year.
Environmental factors	Z_1	SES	Families' socio-economic status. 1. Other workers. 2. Middle managers. 3. Technicians. 4. General managers. 5. Entrepreneurs.
	Z_2	Unemployed	Percentage of unemployed parents.
	Z_3	Immigrants	Percentage of non-Spanish students.
	Z_4	Annual absenteeism	Percentage of student absences during the academic year (students absent more than 75% of all days).
Outputs	Y_1	Grades	Average test mark obtained by the students in the general sixth grade test.
	Y_2	Passed	Number of students who pass the tests.

In terms of inputs, students usually transform a set of resources into heterogeneous outputs. Most of the studies in the literature distinguish between human, capital and physical resources (Hanushek *et al.,* 2013). In this category, we include the number of permanent teachers (X_1) and non-permanent teachers (X_2) (e.g., Hanushek, 1971;

Opdenakker and Damme, 2001; Muñiz, 2002; Cordero-Ferrera *et al.,* 2010; Portela *et al.,* 2013; Johnson and Ruggiero, 2014) and the operational expenses of the school (X_3). We use total operational expenditures as our measure of capital resources under the assumption that, for a given operating environment, higher levels of spending should lead to better outcomes (Blackburn *et al.,* 2014). Many other studies use expenditures as input, which can be cost of personnel or materials (see Grosskopf *et al.,* 1997; Izadi *et al.,* 2002; Oullette and Vierstraete, 2005; Agasisti, 2014; Blackburn *et al.,* 2014; Brennan *et al.,* 2014).

Finally, exogenous variables may have different origins as they can be derived from environmental factors (which include the students' personal characteristics and close family environment) or complexity factors (variables reflecting diversity inside the school) (Harrison *et al.,* 2012). In line with the literature, we include two variables to capture the student's home background: parents' socio-economic status (SES)[10] (Z_1) (e.g., Deller and Rudnicki, 1993; Mancebón and Muñiz, 2008; De Witte and Kortelainen, 2013) and the percentage of unemployed parents (Z_2) (e.g., Mayston and Jesson, 1988; Deller and Rudnicki, 1993; Bradley *et al.,* 2001; De Witte and Kortelainen, 2013). Finally, we incorporate two variables related to the complexity inside the school: the percentage of immigrants (Z_3) (e.g., Jesson *et al.,* 1987; Ganley and Cubbin, 1992; Rubenstein *et al.,* 2007; De Witte and Kortelainen, 2013), and annual absenteeism (Z_4) (e.g., Bessent *et al.,* 1982; Chalos, 1997; Duncombe *et al.,* 1997).

Descriptive statistics are provided in Table 3.2. As can be seen, schools have an average of 21.660 permanent teachers, while the number of non-permanent teachers falls to 5.220. This information shows that the education system in this area basically consists of teachers with stable contracts. In addition, students score an average of 67.135 points out of 100 in the sixth grade final tests. At these levels of education most students usually pass, although there are some who do not reach scores of 50. Non-discretionary factors reveal interesting aspects. First, a high percentage of parents are unemployed and those who are working have a technical profession.

[10] We have data about parents' education level and the socio-economic status (SES). The literature review conducted in Chapter 2 reveals that prior empirical papers have used these measures indiscriminately. However, as there is a high correlation between them ($\rho = 0.683, \alpha = 0.05$), we chose SES due to the higher impact on students' results.

Table 3.2. Descriptive statistics: Public Schools in Catalonia, 2009/2010

Variable	*N*	*Min*	*Q25*	*Mean*	*S.D.*	*Median*	*Q75*	*Max*
X_1	161	4.000	16.000	21.660	7.384	24.000	28.000	35.000
X_2	161	0.000	3.000	5.220	3.307	4.000	7.000	15.000
X_3	161	3,458.459	8,698.015	10,000.873	2,496.390	10,388.902	11,306.439	18,377.685
Y_1	161	38.281	58.725	67.135	9.166	67.442	73.842	88.001
Y_2	161	45.000	238.000	359.730	119.981	414.000	451.500	595.000
Z_1	161	1.000	1.442	2.096	0.456	2.246	2.916	5.000
Z_2	161	0.052	0.113	0.147	0.051	0.139	0.173	0.326
Z_3	161	0.000	0.040	0.133	0.146	0.084	0.177	0.705
Z_4	161	0.000	0.000	0.004	0.009	0.001	0.030	0.079

Second, we find a great variety in the percentage of immigrants. In some schools only 4% of the students are immigrants whereas others have up to 70%. This indicates that our sample contains so-called 'ghetto schools' where a large percentage of immigrants are concentrated. Finally, absenteeism rates are low on average, although there are schools where up to 7% of students leave before the end of the academic year.

Table 3.3 presents the correlation matrix among input and output variables. We conducted a multicollinearity study to detect possible significant relationship and collinearity problems. Both the Tolerance and VIF tests show values that are not disturbing. In all the cases Tolerance is higher than 0.3 and VIF is lower than 3 (see Belsley *et al.* (1980) for thresholds). Therefore, collinearity problems are not an issue in our data.

Table 3.3. Correlation Matrix

Variable	X_1	X_2	X_3	Y_1	Y_2	Z_1	Z_2	Z_3	Z_4
X_1	1								
X_2	-0.063	1							
X_3	0.689*	0.526*	1						
Y_1	0.425***	0.206***	0.638***	1					
Y_2	0.903***	0.243***	0.790**	0.397***	1				
Z_1	-0.091	-0.277***	-0.248***	0.577***	0.132*	1			
Z_2	-0.369**	0.093	0.125***	0.177**	0.396***	-0.674**	1		
Z_3	0.083	0.310***	0.063***	-0.412***	-0.138*	-0.587**	0.429**	1	
Z_4	-0.154	-0.095	0.107*	-0.355***	-0.211***	-0.393**	0.212**	0.468*	1

Notes: ***, **, and *: Below the 1%, 5% and 10% statistical significance thresholds, respectively.

3.5. Results and discussion

3.5.1. CDEA results

In this section we outline the results obtained using the CDEA models from Eq. (3.1) and Eq. (3.2) to estimate the overall efficiency score of our sample. Table 3.4 presents different models of CDEA by changing the sample size. Each column indicates the model we are using, the number of schools operating, the overall efficiency score and the benchmarked schools. Columns 4 and 5 are the most important as they reflect the application of middle- and short-term policies, respectively.

When we apply the short-term policy (Model from Eq. (3.1)) we obtain the result in column 5. Thus, the overall efficiency of the group is 0.873, showing that we could obtain the same outputs even if we save 12.7% of the transferable inputs by maintaining the number of schools operating. To do this, schools should mimic the structure of schools 126 (61 times), 139 (51 times) and 151 (49 times).

Table 3.4. Results of CDEA models

Column	1	2	3	4	5	6	7	8	9	10	11
Model	(3.2)	(3.2)	(3.2)	(3.2)	(3.1)	(3.2)	(3.2)	(3.2)	(3.2)	(3.2)	(3.2)
Schools	(0.7)n	(0.8)n	(0.9)n	n*	n	(1.2)n	(1.4)n	(1.6)n	(1.8)n	(2)n	(3)n
Overall Efficiency (θ)	0.867	0.835	0.838	0.828	0.873	0.928	0.932	0.946	0.955	0.977	0.993
DMU (λ)											
35	0	0	0	0	0	0	0	0	0	0	41
118	87	0	0	0	0	0	0	0	0	0	0
126	26	54	61	58	61	41	50	58	58	58	0
139	0	44	50	52	51	51	24	0	0	0	0
148	0	0	0	0	0	0	0	0	0	120	352
149	0	0	0	0	0	0	0	6	58	0	0
151	0	31	34	36	49	101	68	37	10	0	0
156	0	0	0	0	0	0	0	0	0	24	89
161	0	0	0	0	0	0	83	157	164	120	0
Σλ	113	129	145	146	161	193	225	258	290	322	483

However, according to Mar-Molinero *et al.* (2014) and the current economic scenario in Catalonia, there are situations in which the decision maker can change the assignment of inputs by merging the most inefficient units or opening new units. In the current context of budget constraints, the government requires maximum cost reductions, so the most inefficient units could be merged and the non-permanent teachers could be dismissed. To do this, we run the model from Eq. (3.2) (middle-term policy) by changing the value of n each time (range from $n = (0.7)n$ to $n = (3n)$). Feasible solutions do not exist for $n < (0.7)n$, and $n > (3)n$. This means that it would be impossible to obtain the current output level with fewer than 113 schools.

Although $n = 161$ is a feasible solution, it is possible to improve the results if we reduce the number of operational schools. The global minimum ($\theta = 0.828$, column 4 of Table 3.4) is reached when $n^* = 146$. This implies that 15 schools should be merged with other neighboring schools in order to improve the overall efficiency of the education network by 17.2%. In this case, the cloned schools would be schools 126 (58 times), 139 (52 times) and 151 (36 times). Thus, we can confirm these schools should be taken as benchmarks for reallocation interventions.

Prior to continuing with the reallocation process it is worth noting some features of the benchmark schools. Most significantly, schools 126, 139 and 151 are large in size and students obtain good marks in the general tests. Furthermore, the families' socio-economic level is high. However, the unemployment level is also considerable. At an internal level, these schools have a very low level of absenteeism and a low percentage of immigrants. These features make schools 126, 139 and 151 good benchmarks for the rest.

An important finding is obtained from this information: if the permanent teachers and students at the 15 schools candidates to be merged are reallocated, the remaining 146 schools will be enlarged. Therefore, we demonstrate the existence of increasing returns to scale (IRS) in this education network. That is, we obtain a new network composition that consists of schools with a higher student-teacher ratio, but without altering students' outcomes. This finding is in line with the strategy announced by the government noted in the introduction and Section 3.4.1. However, our model is selective in the reallocation of the available resources and budget. Indiscriminate cuts are not made to the entire network; we only penalize the poorest performers.

This management mechanism would introduce internal competition among schools, and those that did not achieve good results would be penalized. The economic theory suggests that competition should improve school performance by providing incentives for their efficiency and effectiveness (Agasisti, 2011c). Through this process, we have created a performance-based scheme of regulation that introduces incentives and motivates schools to perform effectively.

3.5.2. Resource reallocation. Simulation results

This section details the reallocation process according to the middle-term policy we described in Section 3.1 and the result obtained in Section 3.5.1 using CDEA (model from Eq. (3.2) column 4 in Table 3.4).

Under the middle-term policy only non-permanent teachers can be dismissed and permanent teachers are transferable resources. Following the results of the model from Eq. (3.2) and in accordance with the strategy of the Department of Education, we have to reallocate permanent teachers and students from the 15 merged schools (most inefficient schools) to surviving neighboring schools that have a similar environment. In order to decide which schools are candidates to be merged, we use the conditional and robust order-m efficiency model explained in Sections 3.3.2 and 3.3.3. Table 3.5 shows the descriptive statistics of the efficiency estimation. In this case, recall that we estimate the model using an output orientation (see footnote 6 for further details). Following Daraio and Simar (2005, 2007a, 2007b), we estimate the value of m as the level for which the percentage of super-efficient observations decreases only marginally. Indeed, if m is small the probability of drawing the evaluated observation is rather low, and consequently, we will observe more super-efficient observations. In our application, we selected m = 50. For statistical inference, we use 200 bootstrap replications.

Table 3.5. Efficiency estimates

Variable	***N***	***Min***	***Q25***	***Mean***	***S.D.***	***Median***	***Q75***	***Max***	***Super-Efficient units***	***Efficient units***
$\hat{\theta}_m$	161	0.855	0.995	1.172	0.090	1.151	1.206	1.402	6 (3.723%)	119 (73.913%)

Focusing on the relative performance of schools controlling for exogenous variables, we note that the average efficiency score is $\hat{\theta}_m$= 1.172. Thus, inefficient schools could improve their performance by 17.2%, on average, to achieve the efficiency levels of the best practices. Likewise, six schools have an efficiency score below 1, and can be identified as the best performers in the sample. These super-efficient schools are performing better than the average 50 units they are benchmarked with.

Before explaining the reallocation process, it is worth pointing out the social cost of reallocating resources by merging less efficient schools if this simulation exercise were to be carried out. This cost refers to the reallocation of permanent teachers and students to operating schools. Bearing in mind our assumption that no cost is entailed in transferring permanent teachers and dismissing non-permanent teachers, extra effort was made to minimize these side effects, in an attempt to attenuate the possible associated transportation costs. Teachers and students were therefore reallocated to nearby schools.

The proposed reallocation process is conducted as follows. First, we rank all schools in our sample by efficiency score and selected the 15 schools with the lowest performance score. Second, we compared each surviving school with a more efficient peer (benchmark schools 126, 139 and 151) in order to calculate the differences in terms of students and permanent teachers. This procedure gives us the capacity of reception of each school that would be included in the new network. Then, using the schools' geographical coordinates, we calculated the distance (in kilometers) between each candidate for merger and the rest of the sample. Finally, we listed schools by distance, in ascending order, to reallocate students and permanent teachers to the closest schools. This is an iterative and dynamic process, so after reallocating the resources of each school, we proceeded to recalculate the reception capacity of the rest.

Through this process a total of 5,814 students and 380 permanent teachers were reallocated to neighboring schools, considering that nobody should have to travel more than four kilometers. The total number of non-permanent teachers in our sample is 943. The model from Eq. (3.2) (column 4 in Table 3.4) establishes that it is possible to save 17.2% of them without losing outputs. This percentage represents 163 teachers and the number of non-permanent teachers from the 15 candidate schools for merger is exactly the same, 163. Therefore, these 163 non-permanent teachers are the candidates for dismissal. Table 3.6 shows a sample of how to carry out the reallocation process.

Table 3.6. Example of reallocation process

DMU	PEER	PEER		BEFORE		RECEPTION CAPACITY		REALLOCATION		AFTER	
		Stud.	Teach.	Stud.	Teach.	Stud.	Teach.	Stud.	Teach.	Stud.	Teach.
9	126	463	27	257	18	206	9	100	6	357	24
12	139	415	15	391	22	30	-7	24	0	415	22
13	126	463	27	475	28	-12	-1	0	0	475	28
17	139	415	15	364	19	51	-4	30	0	394	19
18	151	175	10	138	12	-37	-2	17	0	155	12

As can be seen, the system assigns students and teachers according to the reception capacity of each school compared to the peer (the benchmark). Typically, fewer students than the school can receive are reallocated to account for new students that arrive each academic year. For instance, some schools receive both students and teachers (such as DMU 9); others only receive students (such as DMUs 12, 17 or 18) and others like DMU 13, whose current composition is very close to the peer, receive neither students nor teachers. Therefore, our simulation procedure does not penalize the best performers.

We end this section by acknowledging the restrictive nature of the middle-term policy we propose. While it is an efficient cost-saving approach, it is still restrictive as it forces the closure of the worst performing schools. It should be noted that other forms of management could improve the results of the current education network without having to merge any schools. The way to enable these choices lies in transparency and accountability (e.g., Grosskopf and Moutray (2001) study the performance of public schools in Chicago based on decentralization policies). An example, already implemented in the United States, is the publication of Inspectors' evaluation reports (Roderick *et al.,* 2002).

A further example is in the United Kingdom, where the *Office for Standards in Education* (OFSTED) publishes its annual school inspection reports and the annual statistics for education institutions are also published by the *Higher Education Statistics Agency* (HESA). This mechanism introduces competition and motivates schools to work effectively without penalizing them. The publication of such reports disciplines schools because they are aware of the consequences of poor performance (parents do not choose them, and they cannot be sustained in the future). Notwithstanding the importance of this issue, the limitations of the Spanish education system prevent us from addressing it in depth.

3.6. Conclusions

The main goal of this chapter has been to propose a method to assess and re-design a group of schools in a public education network to make additional savings in the education budget. We also reallocated human resources through a new education network composition to optimize overall efficiency without jeopardizing the level of educational quality. We applied the model in a sample of 161 schools from the public education network in Catalonia. We paid particular attention to different policies the decision maker can apply to improve the overall efficiency of the system and reduce expenses. To this end, we extended the CDEA model developed by Lozano and Villa (2004) and Mar-Molinero *et al.* (2014) in order to include the specific treatment of transferable and non-transferable resources, and environmental factors.

The study presents different input oriented CDEA models in order to obtain efficiency improvements inside the education network in line with the strategy established by the government, and bearing in mind the current economic situation. We find that the current education network is inefficient. Specifically, under the short-term policy, results from model (3.1) indicate that without modifying the number of schools operating, the education system could save 12.7% of its transferable resources (non-permanent teachers). However, if we try to optimize the performance of the network (middle-term policy, model (3.2)) the system should consist of 146 schools instead of 161, which would mean a saving of 17.2% of the resources in the form of candidates for dismissal (non-permanent teachers). The remaining permanent teachers and students could be reallocated to schools with suitable reception capacity, considering distance constraints between them.

One interesting finding emerges when simulating the reallocation of permanent teachers and students from the 15 schools to be merged. This procedure would enlarge the remaining 146 schools, thus proving the existence of IRS. By resizing of the network in this way, we would achieve a new composition consisting of schools with a higher student-teacher ratio without altering the students' results. This result supports the government strategy; however; our model is selective in the reallocation of available resources and budget. Indiscriminate cuts are not made in all schools since only the worst performers are penalized.

These conclusions might have important implications for management practices. They establish the necessary actions to optimize the network and to optimally redistribute the available budget. Thus, the decision maker would have an objective justification for strengthening the efficient schools and incentives for supporting less efficient units. From the empirical point of view, the extended CDEA we propose overcomes the problem of including non-transferable inputs and environmental factors, aspects that have not been included in previous research. Finally, this study goes beyond a methodological application of a data set since it proposes an implementation involving a real case, so the applicability of the results is highly illustrative.

Despite the practical implications, this study undertakes a simulation analysis about reallocation. It would be very fruitful to undertake a longitudinal analysis to see how the reallocation and merging process would affect the performance of schools that continue operating after applying this procedure. This would provide additional evidence about the effect of mergers on efficiency. As we noted in the introduction, few empirical papers have addressed this issue in the literature to date (e.g., Skodvin, 1999; Harman, 2000; Hu and Liang, 2008; Mao *et al.,* 2009; Gordon and Knight, 2009; Johnes, 2014). However, there is no real data about reallocations in Catalonia due to the fact that this study is a simulation exercise.

As can be deducted from this chapter, there is an overall inefficiency in the education system because of the management itself. However, environmental factors play a key role analyzing the efficiency in education, since such factors are a potential source of inefficiency (Muñiz, 2002). In this chapter, we have dealt with this issue in both estimations we conducted, the CDEA and the order-*m* model to decide which the worst performing schools were in order to design the reallocation process. Nevertheless, we have carried out this analysis in a sample of schools belonging to a particular educational region, *Vallès Occidental*. The next step is to conduct this evaluation of efficiency throughout the entire public education network in Catalonia, in order to carry out a robust analysis of schools' performance, taking into account the effect of the environment.

With this purpose, Chapter 4 applies the robust conditional order-*m* efficiency model presented in Sections 3.3.2 and 3.3.3 to estimate the role of external factors on the academic performance of schools. As has been derived in Chapters 2 and 3, it is necessary to properly quantify the influence of environmental variables on student outcomes. It will reveal the underlying mechanisms which drive the efficiency estimates, and make more accurate estimates. Recent approaches such as the conditional efficiency model are suitable for this purpose. In Chapter 4 we develop two efficiency estimations, with and without considering environmental factors. Then non-parametric regressions are performed to disentangle the effect of environmental factors on academic performance.

CHAPTER 4.

THE EFFECT OF ENVIRONMENTAL FACTORS ON STUDENTS' ACHIEVEMENT

4. THE EFFECT OF ENVIRONMENTAL FACTORS ON STUDENTS' ACHIEVEMENT

4.1 Introduction

As we stated in Section 1.2, the third research objective of this thesis focuses on the role played by exogenous factors on educational outcomes. Although the literature on this topic is extensive (detailed in Chapter 2), the direction of this relationship is not always obvious (Sirin, 2005).

One goal in the literature on efficiency in education is to define the relationship between educational inputs, environment and achievement. Non-discretionary or environmental variables account heavily for differences in academic results. One of the main (and most controversial) conclusions of the Coleman Report (1966) was that educational resources explained only 10% of academic results, while the remainding percentage depends on other economic variables and the students' family environment. The principal analytical focus in the mainstream education efficiency literature has been to study, through different methodological approaches, the influence of structural, institutional and socio-economic variables on efficiency scores (Worthington, 2001; Johnes, 2015).

As shown in Section 2.2.3.3, different categories of non-discretionary variables can be identified at student and family level, education institution level, and community level. Specifically in terms of family variables, the parents' socio-economic status is a key environmental variable in determining students' results. There is a general consensus that these variables are predictive of educational achievement (e.g., Coleman, 1966; Ruggiero, 1998; Muñiz *et al.,* 2006). However, the underlying question is how these factors might affect school efficiency. Most authors conclude by saying that the higher the parents' status or level of education, the better the results obtained by their children (e.g., Cherchye *et al.,* 2010; Blackburn *et al.,* 2014). Nevertheless, the literature is not unanimous in its conclusions about this relationship (e.g., Muñiz, 2002; Corman, 2003; Ouchi, 2003; Cordero-Ferrera *et al.,* 2010).

In this discussion, our objective is to analyze, using a detailed database, whether an unfavorable socio-economic background always has a negative impact on students' performance.

To this end, we use the robust order-*m* methodology for efficiency assessment (Cazals *et al.,* 2002) described in Chapter 3 to avoid some of the main drawbacks of non-parametric methods such as DEA. This approach consists of constructing a partial frontier using only *m* observation from the sample to determine the efficiency score; thus, the impact of potential outliers in the data is reduced. Subsequently, we employ the conditional non-parametric approach proposed by Dario and Simar (2005, 2007a, 2007b) to incorporate the effect of environmental factors into the estimation of efficiency scores and explore their potential influence without assuming the typical restrictive separability condition of two-stage approaches. As we detailed in Sections 3.3.2 and 3.3.3 of this thesis, both approaches have been applied previously in many empirical studies with educational data for different settings (e.g., Bonaccorsi *et al.,* 2006; Cherchye *et al.,* 2010; De Witte *et al.,* 2010, 2013; De Witte and Kortelainen, 2013; Thieme *et al.,* 2013; among others). We then explore the significance of the impact of environmental conditions on efficiency by developing a non-parametric regression between the ratio of conditional and unconditional efficiency estimates to the environmental factors. Finally, a significance test is performed to disentangle the direction of this relationship.

The data used in our empirical analysis was retrieved from the same source as Chapter 3, the Evaluation Council of the Education System in Catalonia. The sample includes 1,694 primary public schools for the academic year 2009-2010, covering more than 74% of the entire education network. The relevant unit of observation is the school. The dataset contains a wide range of variables. One of its main advantages is that it aggregates information about all the students enrolled in each school, not a random sample, thereby avoiding the selection bias problem.

The most stricking implication of our results is that, even in the worst environment, the internal management of the school has a substantive impact in determining students' efficiency, i.e., school inputs and organization matter.

The remainder of the chapter is structured as follows. Section 4.2 describes the methodology. Section 4.3 explains the main characteristics of the data and the variables selected for the empirical analysis. We present the main results and relate them to the existing literature in Section 4.4. Finally, the chapter ends with some concluding remarks.

4.2 Methodology

As mentioned previously in this thesis, throughout Chapters 3, 4 and 5 we apply the same efficiency assessment approach, the robust order-*m* model (explained in Section 3.3.2). Our choice for this order-*m* model is based on its robustness to the existence of errors in the sample and the presence of outliers. In addition, we apply a conditional approach (explained in Section 3.3.3) due to the fact that this model overcomes the limitations of second-stage models, considering the inclusion of environmental factors at the same stage without assuming the restrictive separability condition.

Although the model has already been explained in Chapter 3, it is worth recalling its basics features in order to explain the method we use to estimate the impact of environmental factors.

4.2.1 Unconditional and robust order-*m* model

Continuing with the notation introduced in Section 3.3.1, students transform a set of inputs $x \in \mathbb{R}_{+}^{i}$ into heterogeneous outputs $y \in \mathbb{R}_{+}^{k}$. In this framework, the production technology is the set of all feasible input-output combinations:

$$\Psi = \{(x, y) \in R_{+}^{i+k} \mid x \text{ can produce } y\} \tag{4.1}$$

An observed production unit defines an individual PPS which, under the free disposability of inputs and outputs, can be written as:

$$\Psi\,(x_j, y_j) = \left\{(x, y) \in \mathrm{R}_{+}^{i+k} \mid x_j \geq x; y \leq y_j\right\} \tag{4.2}$$

In order to estimate the relative efficiency of each school, we estimate a frontier following the ideas developed by Farrell (1957). Specifically, the output-oriented order-*m* efficiency score ($\hat{\theta}_m$) can be obtained from Eq. (4.3) as follows:

$$\hat{\theta}_m\ (x,y) = \sup \theta|(x,\theta y) \in \Psi_m(x) = E\ [max_{j=1,\dots,m}\ \{min_{k=1,\dots,K}(\frac{y_j^k}{y^k})\}|X \leq x] \qquad (4.3)$$

where $\Psi_m(x) = \{(x', y) \in \mathrm{R}_+^{i+k} |\ x' \leq x, i = 1, \dots, m\}$.

This estimator compares the efficiency of a DMU with the m potential observations that have a production larger than or equal to y. An efficiency score equal to one means that the DMU is efficient. A score higher than unity indicates that the unit is inefficient. Lastly, when $\hat{\theta}_m < 1$, the DMU is labeled as super-efficient.

As can be seen, this model does not account for environmental factors. To do so, we apply the conditional approach described in the next section.

4.2.2 Conditional and robust order-*m* model

Once we have obtained the unconditional efficiency score for each school, the next step in our analysis is to consider the effect of some exogenous variables $z \in \mathbb{R}_+^e$. If we do not take into account the existing heterogeneity among schools, we would be implicitly assuming that all the schools are operating with the most favorable environment, which would not be real in many situations (Ruggiero, 1996a; Cordero *et al.,* 2015c). In our case, we are interested in testing the potential influence of some external variables at school level. For that purpose, we use the full non-parametric conditional approach developed by Cazals *et al.* (2002) and Daraio and Simar (2005, 2007a, b), which assumes that both types of factors can have a direct influence on the shape of the best practice frontier (i.e., this model does not assume a separability condition). Therefore, efficiency estimates are determined by inputs, outputs and exogenous variables.

Using a probabilistic formulation, the efficiency measure defined above in Eq. (4.3) has to be adapted to the condition $z = Z$ as follows:

$$\hat{\theta}_m\ (x,y|z) = \sup \theta|(x,\theta y) \in \Psi_m(x|z) = \sup\{\theta|\ S_Y(\theta y|x,z) > 0\} \qquad (4.4)$$

where $\Psi_m(x|z) = \{(x', y) \in \mathrm{R}_+^{i+k} |\ x' \leq x, z = Z, i = 1, \dots, m\}$ and $S_Y(y|x,z) = Prob(Y \geq y|X \leq x, Z = z)$.

To estimate the conditional model, smoothing techniques are needed in *z.* The following kernel estimator of $S_Y\ (y|x,z)$ is used for this purpose:

$$\hat{S}_{Y,n}(y|x,z) = \frac{\sum_{j=1}^{n} I(x_j \leq x, y_j \geq y) K_{\hat{h}}(z, z_j)}{\sum_{j=1}^{n} I(x_j \leq x) K_{\hat{h}}(z, z_j)} \tag{4.5}$$

where $K_{\hat{h}}(\cdot)$ represents the kernel function, $I\ (\cdot)$ is an indicator function and h is an appropriate bandwidth parameter for this kernel. In this case, as in Chapter 3, we follow the data-driven selection approach developed by Badin *et al.* (2010) to estimate the bandwidth parameter h and we use a multivariate kernel function (developed by De Witte and Kortelainen, 2013) since we have mixed data in our data set. Specifically, we employ the Epanechnikov kernel function ($K_{\hat{h}}(z, z_j) = h^{-1}K(\frac{z,z_j}{h})$) for continuous variables and the Li and Racine (2007) discrete kernel function for ordered variables. Finally, the conditional order-*m* estimator $\hat{\theta}_m(x,y|z)$ can be obtained by plugging in the new $\hat{S}_{Y,n}(y|x,z)$ in Eq. (4.4).

4.2.3 Explaining the effect of environmental factors on efficiency

In line with the main goal of this chapter, and following our empirical strategy, the last step entails an analysis to further our knowledge about the direction of the effect of exogenous variables on the production process.

The conditional approach allows us to do that by comparing conditional with unconditional measures. Specifically, we first compute the ratio between the two measures ($R^z = \frac{\hat{\theta}_m(x,y|z)}{\hat{\theta}_m(x,y)}$). Then, as Daraio and Simar (2005, 2007a) suggest, we obtain the scatter plot of this ratio against Z and its smoothed non-parametric regression line. In an output-oriented conditional model, an increasing regression line will indicate that Z is favorable to efficiency whereas a decreasing line will denote an unfavorable effect.

Although this can be very illustrative, it is also possible to check the statistical significance of Z by explaining the variations of R^z. To that end, we follow the proposal by De Witte and Kortelainen (2013) and use local linear least squares for regression estimation, and then apply the non-parametric regression significance test proposed by Li and Racine (2004) and Racine and Li (2004), which smooths both continuous and discrete variables[11].

After running the regression, we test the significance of each continuous and discrete variables using bootstrap tests proposed by Racine (1997) and Racine *et al.* (2006), which can be seen as the non-parametric equivalent of standard *t*-tests in ordinary least squares regression (OLS). However, non-parametric tests are more general than a standard *t*-test (De Witte and Kortelainen, 2013).

4.3 Data and Variables

The data for this study come from the Evaluation Council of the Education System in Catalonia. The relevant unit of observation is the school and the data refers to the academic year 2009/2010. To perform this analysis, we have data on 349,143 students and 1,694 schools distributed across ten REA as shown in Table 4.1.

Table 4.1. Distribution of students and schools by REA

REA	Number of schools	Number of students
A1. Baix Llobregat	153	51,455
A2. Barcelona comarques	155	45,395
A3. Catalunya central	153	31,047
A4. Consorci d'Educació de Barcelona	169	49,442
A5. Girona	232	51,871
A6. Lleida	226	27,089
A7. Maresme	190	57,398
A8. Tarragona	183	42,775
A9. Terres del Ebre	73	13,760
A10. Vallès Occidental	160	56,309
Catalonia	**1,694**	**379,143**

This dataset provides a large amount of information referring to the main determinants driving educational performance, represented by variables associated with family and educational environments as well as school management and educational supply. Since the landmark Coleman Report (Coleman, 1966) and as

[11] See De Witte and Kortelainen (2013) for a detailed explanation of non-parametric regression and its advantages.

noted in Chapter 2, it has become common to group the variables involved in the school production process into three categories: outputs, inputs and environmental factors.

Table 4.2 reports the definition of each variable. Note that we use the same specification of the efficiency model as in Chapter 3, but in this case we add information about several environmental variables, since they constitute the core of this analysis.

Table 4.2. Description of variables

Category	Variable		Description
Inputs	X_1	Teachers	Total number of teachers working at the school.
	X_2	OPEX	School operational expenses in the academic year.
Outputs	Y_1	Grades	Average test mark obtained by the students in the general sixth grade test.
	Y_2	Passed	Number of students who pass the tests.
Environmental factors	Z_1	SES	Families' socio-economic status. 1. Other workers. 2. Middle managers. 3. Technicians. 4. General managers. 5. Entrepreneurs.
	Z_2	Unemployed	Percentage of unemployed parents.
	Z_3	Immigrants	Percentage of non-Spanish students.
	Z_4	Annual absenteeism	Percentage of student absences during the academic year (students absent more than 75% of all days).
	Z_5	Educational needs	Percentage of students with special educational needs (autism, personality disorder behavior, psychological, motor, auditory or visual impairment, Down's Syndrome, exceptionally gifted).
	Z_6	Late incorporation	Percentage of newly incorporated students (halfway through the year).
	Z_7	Teachers' mobility	Percentage of teacher turnover (newly incorporated teachers plus those who leave the school).

As in Chapter 3, our output indicators are test scores and number of students who pass the tests. As Hoxby (2000b) states, the most important reason to choose this proxy as an output could be that both policy makers and parents use this criterion to evaluate school performance. Specifically, as our unit of analysis is the school, we consider the the arithmetic mean of the students' grades in the sixth grade general tests conducted in Catalonia (*Grades*) and the number of students who pass the exams (*Passed*).

In terms of inputs, we include two measures that are directly involved with student learning (*Teachers* and *OPEX*). *Teachers* represents the number of academic staff working in the school. The literature reveals that the number of personnel employed is a good proxy for human capital in education institutions (e.g., Haelermans and Blank, 2012, Haelermans *et al.,* 2012; Thieme *et al.,* 2012; Deutsch *et al.,* 2013; Brennan *et al.,* 2014). *OPEX* refers to the operational expenses in each school. We use total operational expenditures as our measure of school capital resources under the assumption that, for a given operating environment, higher levels of spending should lead to better outcomes (Blackburn *et al.,* 2014).

Finally, we considered environmental factors related to the characteristics of schools and students that may influence school efficiency. As we stated in previous chapters, these variables are beyond the control of the school, but can affect pupils' attainment. They may differ in their origins, as they can be derived from environmental or complexity factors (Harrison *et al.,* 2012). In line with the literature, we first include information about the students' socio-economic environment (*SES*) and the proportion of unemployed parents (*unemployed*) (e.g., Mayston and Jesson, 1988; Bradley *et al.,* 2001, 2010; Johnes *et al.,* 2012; Blackburn *et al.,* 2014).

We also incorporate several factors related to the complexity inside the school. Firstly, immigrant status has received increasing attention in the recent literature (see Conroy and Arguea, 2008; Bradley *et al.,* 2010; Gronberg *et al.,* 2012; Johnes *et al.,* 2012; Misra *et al.,* 2012; DeWitte and Kortelainen, 2013; Zoghbi *et al.,* 2013; Crespo-Cebada *et al.,* 2014). In the case of Spain, this is an especially relevant environmental variable due to the growth of the school-age immigrant population during the last decades. We include the percentage of non-Spanish students in the analysis (*immigrants*).

In addition, we introduce the percentage of students with educational needs (e*ducational needs*). Several studies have revealed a growing importance of this factor in determining students' results (e.g., Conroy and Arguea, 2008; Bradley *et al.,* 2010; Naper, 2010; Gronberg *et al.,* 2012; Johnes *et al.,* 2012; Grosskopf *et al.,* 2014).

Thirdly, we include two measures to reflect school attendance: annual absenteeism (*annual absenteeism)* and the percentage of newly incorporated students (*late* *incorporation*). Although attendance rate is something school leaders can attempt to influence to increase efficiency, it is also significantly determined by other agents (e.g., parents, peer group, etc.), which makes it an environmental factor (see Chalos, 1997; Conroy and Arguea, 2008; Zoghbi *et al.,* 2013).

The last factor to bear in mind is teachers' mobility (*teachers' mobility*). Of particular importance for education policy makers is the possibility that teacher mobility adversely affects the quality of teaching in schools. Several studies on teacher mobility have focused on the factors determining the decision to leave the public school system (see Dolton and Van der Klauw, 1995; Stinebrickner, 2002; Hanushek *et al.,* 2004; Bonesrønning *et al.,* 2005) or to move within it (see for example Falch and Strom, 2005 and Scafidi *et al.,* 2007). Specifically, dissatisfied teachers who want to transfer to another school may be poor performers not only because of general motivational factors (Hanushek *et al.,* 2005), but also because they are simply waiting to move on to a different location, and as a result they put less effort into their current work duties and disregard any longer term plans for their students. Barbieri *et al.* (2011) found that teachers systematically try to move away from schools where teaching is likely to be more difficult because of the student mix or the social context of the school.

Table 4.3 reports the main descriptive statistics of inputs, outputs and environmental variables. As can be seen, schools employ, on average, 21.135 teachers, including both permanent and non-permanent teachers. The smallest school has only one teacher whereas the biggest one has 52. The mean *OPEX* is €7,522.810, although the maximum rises to €63,265.625. In terms of outcomes, not all the students pass the aptitude test: we find grades below 50 out of 100. The average grade is 68.325.

Finally, our sample is characterized by a relatively high percentage of unemployed parents, 15.319%, and most of them work in companies as regular workers or technicians. The proportion of immigrants and teachers' mobility is also high, an average of 12.494% and 26.918%, respectively. The absenteeism rate is considerable in some schools, despite the fact that we are dealing with primary education. Lastly, we can confirm that no more than one third of students from one school in our sample present a special educational need.

Table 4.3. Descriptive statistics

Variable	*N*	*Min*	*Q25*	*Mean*	*S.D.*	*Median*	*Q75*	*Max*
X_1	1,694	1.000	12.000	21.135	11.409	20.000	32.000	52.000
X_2	1,694	1,314.964	4,625.203	7,522.810	3,927.862	6,560.390	10,258.412	63,265.625
Y_1	1,694	32.178	62.268	68.325	10.735	70.596	76.011	95.654
Y_2	1,694	4.000	85.250	214.365	147.279	193.500	339.000	685.000
Z_1	1,694	1.000	1.431	2.075	0.416	2.698	2.960	5.000
Z_2	1,694	0.000	11.020	15.319	7.644	11.020	18.134	100.000
Z_3	1,694	0.000	4.588	12.494	11.461	9.099	17.236	74.262
Z_4	1,694	0.000	0.000	1.002	2.375	0.000	0.898	23.762
Z_5	1,694	0.000	0.000	1.896	2.867	0.947	2.417	28.571
Z_6	1,694	0.000	0.000	1.621	3.835	1.000	1.852	90.000
Z_7	1,694	0.000	15.000	26.918	18.711	25.000	36.922	100.000

Table 4.4 presents the correlation matrix among variables. Given the large number of non-discretionary factors defining the internal and external environment of the school, we conducted a multicollinearity study to detect significant relationships and collinearity problems. Both the tolerance and VIF tests show values that give no cause for concern. In all the cases tolerance is higher than 0.3 and VIF is lower than 3 (see Belsley *et al.,* 1980 for thresholds).

4.4 Results and discussion

The results of the efficiency estimations for both unconditional and conditional models are summarized in Table 4.5. As stated in Section 4.2, in both cases, we estimate the robust order-*m* model using an output orientation. Concerning the value of the parameter *m*, which determines the sample size for comparisons, we again followed the criterion established by Daraio and Simar (2005) and fixed *m* at 100. For statistical inference, we use 200 bootstrap replications.

Table 4.4. Correlation matrix

	X_1	X_2	Y_1	Y_2	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7
X_1	1										
X_2	0.789**	1									
Y_1	0.455***	0.689***	1								
Y_2	0.924***	0.735***	0.354**	1							
Z_1	-0.306***	-0.254***	0.281***	0.158***	1						
Z_2	0.180***	0.142***	0.242***	0.369***	-0.444***	1					
Z_3	0.113***	0.072***	-0.210**	-0.037	-0.394***	0.249***	1				
Z_4	-0.033	0.116*	-0.146**	-0.023	-0.181***	0.109**	0.176***	1			
Z_5	0.014	0.010	-0.016	-0.025	-0.039	0.011	0.076***	0.109***	1		
Z_6	0.019	0.036	-0.153***	-0.043*	-0.143**	0.093***	0.352***	0.099***	0.059**	1	
Z_7	-0.169***	-0.098***	-0.196***	-0.197***	-0.011	0.046*	0.003	0.011	0.001	0.045*	1

Notes: ***, **, and *: Below the 1%, 5% and 10% statistical significance thresholds, respectively.

Table 4.5. Efficiency estimates and bandwidths

	N	Min	Q25	Mean	S.D.	Median	Q75	Max
Unconditional efficiency	1,694	0.870	0.940	1.116	0.300	0.998	1.102	1.870
Conditional efficiency	1,694	0.871	0.937	1.132	0.314	1.000	1.118	1.890
Bandwidth Z_1	1,694	0.060	0.086	0.317	0.186	0.473	0.587	0.612
Bandwidth Z_2	1,694	0.071	0.121	0.344	0.185	0.417	0.549	0.602
Bandwidth Z_3	1,694	0.097	0.311	0.824	2.759	0.856	2.012	3.925
Bandwidth Z_4	1,694	0.162	0.212	0.401	0.229	0.521	0.965	2.866
Bandwidth Z_5	1,694	0.129	0.425	0.523	0.244	0.542	2.423	3.892
Bandwidth Z_6	1,694	0.089	0.167	0.357	0.167	0.421	0.541	0.578
Bandwidth Z_7	1,694	0.054	0.150	0.217	0.307	0.547	0.621	0.635

As can be seen from Table 4.5, the performance of schools without controlling for exogenous variables (unconditional efficiency) amounts to 1.116, on average. Therefore, inefficient units could still improve their performance by an average of almost 11.6% to achieve the efficiency levels of the best practices. Likewise, some schools have an efficiency score below 1, and can therefore be identified as the best performers in the sample. These super-efficient units are performing better than the average 100 units they are benchmarked with. The main problem of this unconditional assessment is that it does not take into account the environment with the result that the efficiency scores may not be adequate. The next step is therefore to estimate the conditional efficiency model which allows us to control for heterogeneity among the characteristics of each school in the sample.

Once we include the environmental variables (Z) in the estimation of the conditional efficiency model, the value rises to 1.132. Thus, it appears that after controlling for the environment, there is more room for improvement. This is an unexpected result, as the standard literature tends to reduce the targets for schools when each unit is only compared with those operating in a similar environment, so the reference set is smaller. For instance, Muñiz (2002) finds that including more environmental factors in the analysis leads the increase of efficient units. Corman (2003) reveals that students' economic background has a positive and significant effect on the probability of repeating a grade. Cordero-Ferrera *et al.* (2010) conclude that when controlling for non-discretionary inputs, schools increase their scores because they were benchmarked in an unfavorable context.

In searching for an explanation for this striking result, we found the work by Ouchi (2003), who shows that poor socio-economic status does not always negatively influence students' outcomes.

Bearing in mind the lack of consensus in the literature, and in order to better explain the underlying mechanism, we test the influence of each exogenous variable by performing a non-parametric regression between the ratio of the estimated efficiency scores ($R^z = \frac{\hat{\theta}_m(x,y|z)}{\hat{\theta}_m(x,y)}$) and the environmental factors (Z). Table 4.6 presents the *p*-values of the significance test proposed by Li and Racine (2004) and Racine and Li (2004).

Table 4.6. Non-parametric significance test

Variable	p-value	Effect revealed from partial plot
Z_1	0.000***	Favorable
Z_2	0.002***	Favorable
Z_3	0.072*	Unfavorable
Z_4	0.100*	Unfavorable
Z_5	0.506	Slightly unfavorable
Z_6	0.074*	Unfavorable
Z_7	0.001***	Unfavorable

The significance tests indicate that all the environmental variables we consider in this study have an impact on school performance, except for the proportion of students with special educational needs, which does not rearch a significant level. As we are interested in knowing the direction of this relationship, we follow the proposal by Daraio and Simar (2005, 2007a) and obtain the partial scatterplots for each *Z.* Since we are examining an output-oriented case, a decreasing regression line indicates that the environmental variable is unfavorable to school efficiency. Figure 4.1 illustrates the partial plot for each variable.

Figure 4.1. Effects of environmental variables on efficiency scores

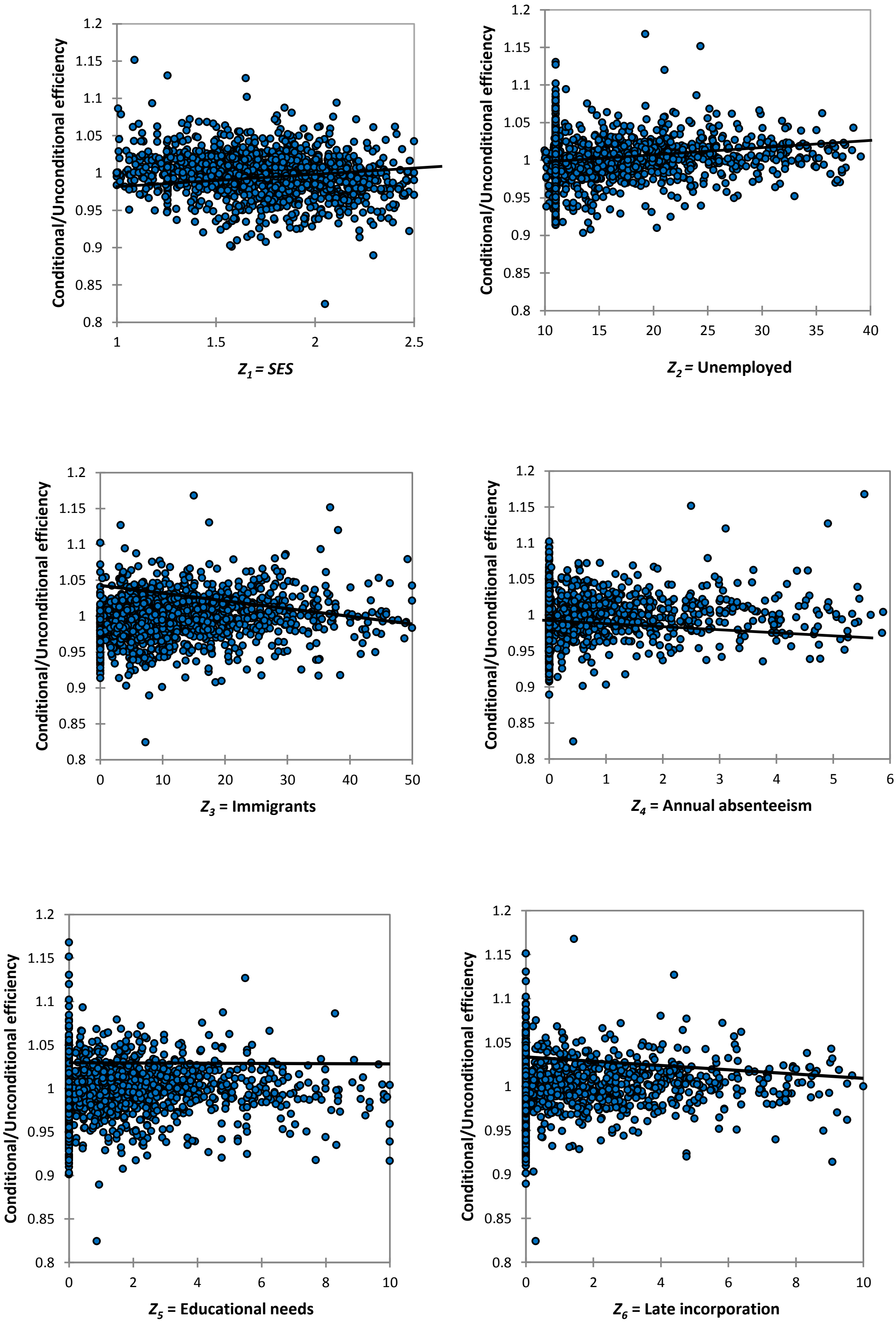
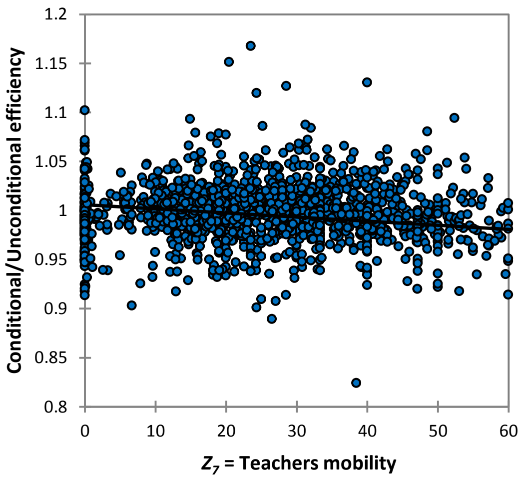


Figure 4.1. Effects of environmental variables on efficiency scores (cont.)



As can be seen from the scatterplots, the effect on the efficiency score is positive and significant for SES. Thus, the higher the socio-economic level, the greater the outcomes the school can achieve. This means that when we compare schools with similar socio-economic environments, the potential output increases. Conversely, the effect of other variables is negative and significant; this is the case of the proportion of immigrants in schools, annual absenteeism, percentage of newly incorporated students, and teachers' mobility. Thus, the larger the value of these factors, the higher the complexity inside the school, which reduces the potential outcomes. These findings are in line with previous literature (e.g., Muñiz, 2002; De Witte and Kortelainen, 2013).

The difference that justifies the higher conditional (in)efficiency score (1.132 in Table 4.5) appears with the variable *unemployed*. This variable positively affects the potential target to achieve and, as a consequence, the larger the number of unemployed parents, the better potential results students can achieve. The phenomena we are capturing is aligned to what Ouchi (2003) found when analyzing US public schools. Ouchi describes how students attending a public school located in a very poor environment (the Goudy School) achieved exceptional results in their general tests. He points out that: *'this school is located in an immigrant neighborhood where 26 languages are spoken. 98% of the students are from low-income homes. However, on the Iowa Test of Basic Skills reading, math and English scores surprisingly rose'* (Ouchi, 2003, p.3-7).

This school managed this turnaround thanks to the commitment of the parents and the school organization. On the one hand, parents encouraged their children to obtain the best grades in order to escape from their negative environment. On the other hand, the principal adopted a participative organization and delegated decisions to the teachers, which helped solve the problems and provided students with a good transfer of knowledge. Ouchi very expressively pointed out that, *'they focused everyone on student achievement, not complaining about the poor children who were in the neighborhood'* (Ouchi, 2003, p.4).

This case study demonstrates that a school's good results are not only a question of environment: parents and teachers also have a role to play. Thus, if a school operating in the worst environment could become one of the best public schools in the US, then every school can be successful. For those who believe that a school made up of families with economic needs or with a high level of unemployment cannot achieve high academic levels, the Goudy school proved otherwise. What Ouchi found, as a partial result obtained from a qualitative case study, now appears to have statistical significance after applying the new robust family of non-parametric estimation methods to the public school network in Catalonia.

4.5 Conclusions

As deduced from the literature review in Chapter 2, there is no unanimous consensus in the literature about the effect of certain environmental factors on student outcomes or school efficiency. For this purpose, various approaches have been used to quantify the effect of these variables on performance (See Simar and Wilson, 2011, for a review of traditional models). However, traditional models applied fail in their estimates partly because of the restrictive separability condition assumed between the inputs-outputs space and the environmental factors space. For this reason, new models have recently emerged aiming to measure the efficiency and the effect of environmental factors, thus overcoming this and other limitations of traditional models. One example is the conditional model.

In this environment, the objective of this chapter has been to analyze, using a detailed database, whether an unfavorable socio-economic background always has a negative impact on students' performance. To meet our goal, we employ the so-called conditional non-parametric approach to estimate efficiency measures for a set of primary schools in Catalonia, incorporating the effect of different environmental factors representing the characteristics of each school. This method allows us to avoid the restrictive separability assumption and thereby provide meaningful results. In addition, this methodology makes it possible to determine the statistical significance and the direction of the effect of the exogenous variables.

The empirical results show that the environmental variables considered (except for the proportion of students with special educational needs) have a significant effect on the performance of primary schools. The direction of the relationship is in line with the results obtained in the previous literature using traditional semi-parametric approaches.

However, the most striking result comes from the fact that when we include the environmental variables in the conditional analysis, the efficiency ratio does not improve as a result of reducing the scope of comparison to schools with similar environments. On the contrary, inefficiency increases from 11.6% to 13.2%, indicating that the scope for improvement increases and the target to achieve (the benchmark) is more demanding. After performing the non-parametric regression and the significance test, we found that the discordant variable refers to the percentage of unemployed parents, which has a favorable and significant effect on efficiency.

Therefore, while perhaps initially surprising, our results support the hypothesis that specific negative environmental factors can positively affect schools' potential outcomes. Thus, a higher percentage of unemployed parents encourages students to improve and try to overcome their limitations at home by focusing on school and not leaving (as Ouchi, 2003, demonstrated through case studies in US public schools). In addition, this result also reveals that teachers and school management play an important role in motivating students to achieve the best results.

The implications for policy implications raised by these results are twofold: public managers could improve results in schools located in poor areas. Thus, it is possible to introduce higher levels of school quality, motivation, and competition within the education system. From the academic point of view, this application shows that schools' performance is not only a question of environment. Parents and teachers play a role in encouraging pupils to improve their results. However, the assessment models used to date did not help to shed light on this issue.

Linking with the first implication of this study, it is necessary to detect in which specific geographical areas schools need to improve their performance through, for example, the promotion of quality in education or through the assignment of additional resources. In turn, it is essential to determine whether or not these policies serve as an incentive to encourage the demand for places in schools in more deprived areas. What is more, if we consider the public education system as a competitive market, it would be very fruitful to know how these policies and parents' reactions influence schools' performance. Furthermore, it is necessary to determine the extent to which these policies have a real impact on the improvement of school results in the long term and whether, as a consequence of their application, schools' technical efficiency increases.

Bearing in mind this reflection, the next two chapters of the thesis provide answers to each question separately. In particular, Chapter 5 supplements previous chapters by evaluating the efficiency of management in public schools including an additional level of analysis: the location of the school. The public education system is not devoid of competition, which may be a result of schools' performance and location. In this vein, the next chapter provides evidence on strategic interaction (competition in location) among public schools. It employs a two-stage estimation procedure to assess whether competition among public schools influences the demand for places in them. A robust conditional order-*m* approach is used to estimate the efficiency of each school (as in this chapter), and then a spatial econometric framework is applied to disentangle the correlation in the demand for a school due to the existence of strategic interaction. Finally, Chapter 6 closes the empirical analysis of this thesis by developing a longitudinal analysis of the effectiveness and efficiency of public schools in the application of a specific quality improvement program undertaken in Catalonia. Specifically, we apply the DiD approach with panel data regressions together with Malmquist TFPC index.

CHAPTER 5.

DOES STRATEGIC INTERACTION IMPACT ON DEMAND FOR SCHOOL PLACES? A CONDITIONAL EFFICIENCY APPROACH

5. DOES STRATEGIC INTERACTION IMPACT ON DEMAND FOR SCHOOL PLACES? A CONDITIONAL EFFICIENCY APPROACH

5.1 Introduction

In the last 20 years, market elements such as increased consumer choice or published performance indicators have been introduced in many areas of public policy, including education. Many OECD countries are introducing school choice reforms with the objective of giving more opportunities for parents to decide for a particular school (OECD, 2011). In this environment, school choice is perhaps one of the most hotly discussed issues in the current education policy debate (Ghosh, 2010; Calsamiglia and Güell, 2014).

The interpretation of school choice is part of a bigger movement within New Public Management (NPM) (Hood, 1995). In this context, the idea behind school choice is based on the reforms that give parents the right to influence the decisions on pupil allocation to schools (Millimet and Collier, 2008). Most countries allow parents and students to select their school from a diverse array of choices. Normally, an initial geographical assignment in elementary school is accompanied by more flexible choice options later on in secondary levels of education in most OECD countries (OECD, 2011). Proponents of NPM argue that choice reforms will lead to stronger sorting, promote competition, and increase accountability in the public education system (Zanzig, 1997; Hoxby, 2000a; Ghosh, 2010). In addition, these NPM-inspired policies have a strong potential to shift school systems to a higher level of efficiency (Rincke, 2006).

Within this framework, a vast literature has emerged attempting to uncover the factors that influence the relationship between competition and efficiency in education from the supply point of view (see Rincke, 2006; Millimet and Collier, 2008, and references within). However, assessments of such competitive effects on the demand for places in public schools are less frequent (e.g., Shumow *et al.,* 1996; Lai *et* *al.,* 2009; Gibbons and Vignoles, 2012). In this environment, the objective of this chapter is to test whether there is strategic interaction[12] in parents' selection for a school within an education system of increasing choices.

In other words, we seek to answer two research questions: First, in an education system with increasing choices, to what extent parents' preference for a public school depends solely on the distance from their residence or whether, on the contrary, this decision is also based on additional criteria like the quality of school management? Having established the school choice process, our second research question deals with the effect of strategic interaction among public schools, specifically we wonder whether the demand for a school is partially explained by competition and its neighbors' performance.

This study answers the above research questions by taking a two-stage approach and examining whether competition among public schools influences demand from parents. As Millimet and Collier state (2008) increased competition impacts on the efficiency of public schooling. Thus, in the first stage we estimate the efficiency of management in each school in the sample by applying a non-parametric and robust conditional order-*m* efficiency approach (Cazals *et al.,* 2002; Daraio and Simar, 2005, 2007a, 2007b). In the second stage we apply a spatial econometrics framework (Anselin, 1988; LeSage and Pace, 2009) to disentangle the existent correlation in the school demand due to this strategic interaction between public schools. The analysis employs some standard spatial econometric models and diagnostic tests, as well as assumptions about the nature of spatial relationships among schools, as captured by a spatial weight matrix.

We develop this analysis using data on public schools in Catalonia. The case of Catalonia is particularly important because it provides a scenario of public schools competing to attract students and resources. The system allowes parents to freely decide up to 10 schools for their children. After submitting their choices in order of preference, a set of established criteria determines the final allocation (for instance,

[12] The term 'strategic interaction' is commonly used in the literature to refer to the interdependence between the units under analysis due to the existence of competition (see Brueckner, 2003 for a survey of the literature). Strategic interaction is said to occur when the levels of variables in one jurisdiction are influenced by the levels of the same variables in neighboring jurisdictions (Ghosh, 2010).

distance to the school, siblings attending the school, or socio-economic variables)[13]. In this environment, parents may decide on a particular school not only based on location or distance, but also based on their personal judgments and past experiences about the quality of school management.

At this point, several questions concerning the sample are worth noting. Firstly, as we stated in Chapter 1, we restrict the empirical development of this thesis to public schools due to the lack of data from private education institutions. Nevertheless, this limitation does not prevent us from conducting the analysis to accomplish our objective. In fact, and following Millimet and Collier (2008, p.135), we focus on competition arising from nearby public schools, and not from other sources such as grant-maintained or private schools, because "*competition from other public schools is the most remarkable type of competition in the status quo*." Hoxby (2002, p. 17) also states that "*this traditional form of [school] choice is by far the most pervasive and important form of choice in elementary and secondary schooling today*." In addition, Hanushek and Rivkin (2003, p. 3) argue that "*the most important element of competition comes from other public schools*".

Secondly, we analyze public schools located in urban municipalities. Following EUROSTAT criterion, municipalities with fewer than 5,000 inhabitants were classified as rural and those with 5,000 inhabitants or more as urban. Rincke (2006) states that public schools in metropolitan areas have stronger competition because they are divided into more school districts. With more schools available, it is easier for households to sort themselves according to preferences for public school choice.

Thirdly, in contrast to most previous research, our relevant unit of observation is the school rather than the district. We are interested in knowing parents' behavior for one school, not for the average demand in the district. Examining individual school level data rather than district or county level data should provide information that has policy implications for improving public education. As Misra *et al.* (2012, p.1180) point out, "*the results from the aggregate level may not reveal correct information on the individual school level, and policy prescription based upon these results may not be*

[13] See the working paper by Calsamiglia and Güell (2014) for more details about the school choice process in Catalonia.

appropriate. To analyze school performance in the education market, one needs to use school level data instead of school district or county data."

The results confirm our hypotheses as we find that first, in an increasing choices enrollment system, parents perceive the quality of school management, and this perception resembles schools' efficiency. This quality of school management is inferred through parents' demand for one school over another in their list of preferences. Therefore, parents take into account not only location when selecting a school for their children, but also their perception of performance. Second, we find evidence that parents' demand for a public school rises with increasing demand for neighboring schools, proving the existence of strategic interaction in public educational market due to competition in location. However, this positive spillover effect diminishes when neighboring schools' performance is included in the analysis. These findings also confirm the existence of competition in performance among public schools in Catalonia. In fact, the results suggest that the impact of neighbors' performance on demand for a school is substantial, and contributes to higher engagement in competition for students and resources.

This study contributes to the existing literature by examining the strategic behavior of demand for places in schools in a competitive public school system. In addition, we add information to the literature examining strategic interaction on public policies in general and on schools in particular. To the best of our knowledge, this is the first study that attempts to explain the behavior of demand for places in public schools using a spatial approach together with efficiency analysis in the Spanish context[14]. As stated below, several papers have used a spatial model to analyze competition arising from neighboring public schools, but few empirical papers have taken into account the impact of strategic interaction on demand for school places. As well as being linked to the growing literature on strategic interactions, this study is also closely related to the literature on the effects of competition on performance. However, we adopt a demand side point of view.

[14] There is recent paper by Vidoli and Canello (2015) which controls for spatial autocorrelation using non-parametric efficiency estimation. However, the authors apply the model with simulated data in Italian industrial districts.

After this introduction, the remainder of the chapter is organized as follows. Section 5.2 revises the literature on school choice and strategic interaction and presents the conceptual model. Section 5.3 outlines the empirical methodology used in the study. Section 5.4 describes the data and the specification of the variables. Section 5.5 discusses the results from different spatial models, and the last section provides some concluding remarks.

5.2 Literature review and hypotheses definition

School choice policies have received increasing attention from researchers and policy makers around the world as an expanded choice can make public schools more efficient (Hoxby, 2000a, 2003). On the demand side of schooling, more choices available indicate that parents have more freedom to choose a school for their children. Apart from the distance to their residence, parents appear to decide on a particular public school based on, among other things, their personal judgments and experiences about the quality of teaching and management. In a previous work, we concluded that parents' intuitions resemble school performance and justify the demand for the school. In this previous study, we use a naïve two-stage semi-parametric approach (DEA (Charnes *et al.,* 1978) together with a OLS regression) in order to explain the drivers of demand for places in public schools. Our purpose here is to reinforce this finding by using a robust non-parametric approach (conditional order-*m* efficiency model). This leads us to first propose the following hypothesis:

> *H1: In an open enrollment system, demand for public schools partially depends on schools' performance.*

Although not with the same components, this hypothesis has been partially tested in previous works (e.g., Handa, 2002). In our humble opinion, students' academic results are not the best choice of indicator as the main driver of school demand. Parents do take into account a wider range of elements than only grades when choosing a school for their children. However, it is true that grades are a significant component of efficiency.

In addition to the quality of management, demand for places in a public school is also explained by location. Schools do not operate in isolation, as they belong to an education system competing each other to attract as many students as they can to justify their budget (Zanzig, 1997).

Given that public schools cannot engage in price competition—competition between public schools focuses on attracting and retaining more and better students—the question to answer would be how an increase in the degree of competition impacts on school performance and demand for places in them. Hoxby (2000a) and Barrow and Rouse (2004) note that, even without private or charter schools, the public education system would not be devoid of competition. Tiebout (1956) confirms that this competition arises through the residential location decisions of households. In addition, Barrow (2002) claims that parents decide on a particular public school through location choice. The main implication of these findings is that public schools already face some competition from other public schools in the area and this can impact on parents' choices. The literature about interdependent decision-making behavior suggests that, when faced with important decisions, economic agents may be influenced by strategic interactions with neighboring decision makers; and might emulate their decisions or respond strategically to them (Brasington *et al.,* 2016).

Hoxby (1999) also argues that school principals usually implement policies according to parents' preferences because what parents are looking for are schools with better resources. In this scenario, school principals try to meet parents' needs by adopting certain plans to attract students (for instance, by implementing specific teaching innovation projects). Therefore, schools that pay more attention to parents' preferences might be more successful in attracting students who are, after all, consumers in the education market place.

The literature about competition among public schools does not reveal much about how parents react to the forces of competition in location when they carry out their choice. A better understanding of the effect of open choice on the behavior of parents is crucial in assessing current reforms and implementing future incentives. Most importantly, more insight is needed into how the demand for places in a public school is affected when it faces increased competition from other public schools in the area. This leads to our second hypothesis:

H2: As part of the strategic interaction among public schools, demand for a school is partially explained by the demand for neighboring schools.

We cannot anticipate the sign of this relationship, as we may find a positive spatial spillover effect in demand, implying that an increase (decrease) in demand for neighboring schools is matched by an increase (decrease) in the demand for the school under analysis. If this is the case in our context, we expect to see clusters of schools with similar demand or other spatial patterns consistent with strategic interactions. This would lead to the "quiet life hypothesis" (Berger and Hannan, 1998), implying that school managers may make less effort to maximize the demand for places in the school. This would be the case of, for example, a school with a low demand located in a good area and whose neighboring schools have a higher demand; this school could easily assume the additional demand its neighbors cannot absorb without any extra effort.

A review of the literature reveals an extensive stream that has addressed the effects of competition on the performance of public schools and on student achievement (see the work of Misra *et al*. (2012) for a literature review of competition studies in education), which contrasts with the lack of research into the effects of competition on the behavior of demand for places in schools (e.g., Shumow *et al.,* 1996; Lai *et al.,* 2009).

The empirical findings suggest that the overall effects of competition on performance are positive. For instance, Blair and Staley (1995) estimate a spatial autoregressive model regressing achievement in a given school district on the average achievement of bordering school districts. The authors find a positive association, but treating achievement in neighboring districts as exogenous ignores the simultaneity that arises in models of spatial reaction functions (Anselin, 2002). Dee (1998) analyzes public versus private school competition and the effects on the quality of public schools. This author finds that competition from private schools does have a positive and statistically significant impact on the high school graduation rates of neighboring public schools. Hoxby (2000a) concludes that competition positively affects student achievement and public school productivity. Grosskopf *et al.* (2001) report that greater competition reduces allocative inefficiency, but not technical inefficiency.

Sandström and Bergström (2005) find that school results in Swedish public schools have improved as a result of competition from independent schools.

Rincke (2006) examines the behavior of local school districts in Michigan after the introduction of a voluntary inter-district school choice program in 1996. He finds evidence that lagged adoptions of school choice in adjacent districts have a significant and positive impact on the districts' probability of participating in the choice program. Millimet and Rangaprasad (2007) examine whether the decisions concerning school inputs are spatially linked across school districts within the same county. Their results confirm the strategic behavior of public schools, but only during periods of binding financial constraints. In a later study, Millimet and Collier (2008) assess whether competition among public schools influences their efficiency. They find a significant amount of inefficiency in public school districts in Illinois, but show that districts respond to incentives, becoming more efficient as neighboring districts increase in efficiency. These authors also argue that competition exists in the public school system even prior to recent policy reforms and without taking private schools into account.

Ghosh (2010) studies whether public school districts respond to the school input decisions of other districts. The results show that public school districts positively respond to the expenditure decisions of neighboring districts, thereby acting strategically when setting their own spending levels. More recently, Agasisti (2011a, 2013) investigates the role of competition in explaining performance in Italian schools, finding that the impact varies according to the functional form of the relationship between the two variables. Finally, Misra *et al.* (2012) use a stochastic frontier approach together with the geographical information system (GIS) approach to develop a competition index and to analyze the relationship between private competition and public school efficiency in Mississippi. They find that higher competition from private schools significantly increases public primary school efficiency.

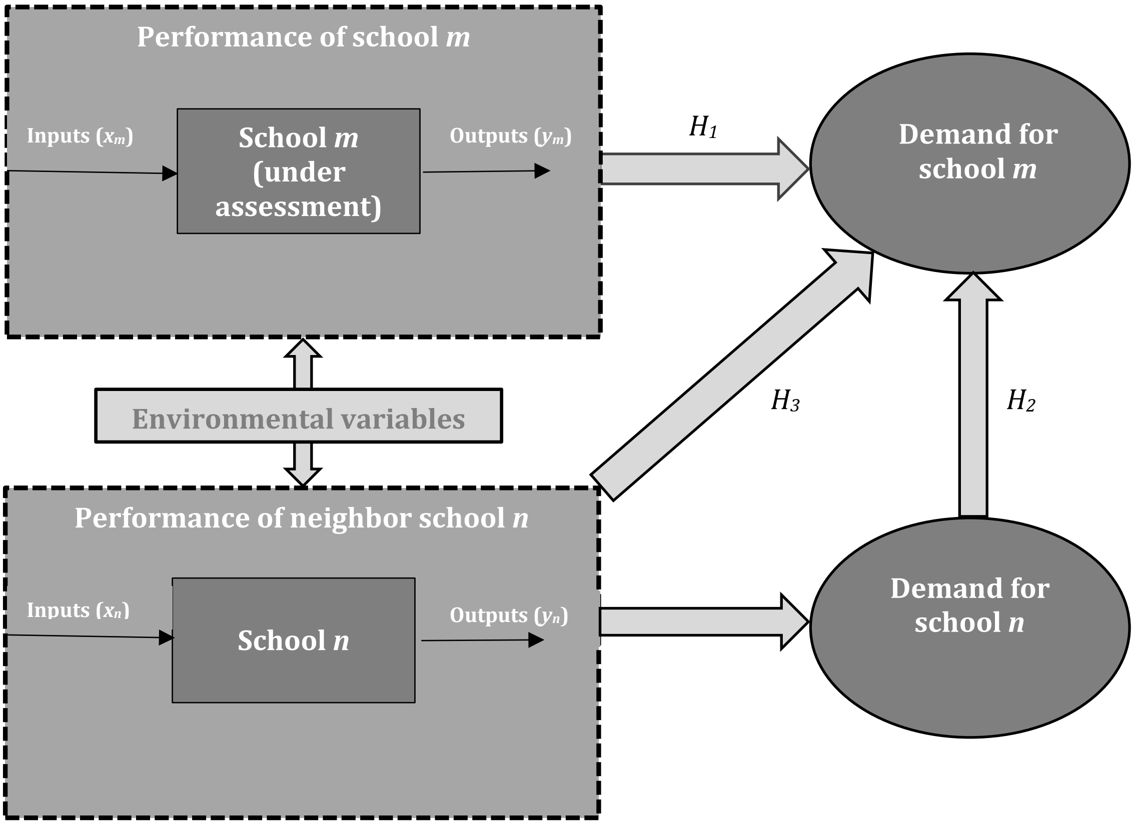
This evidence raises the question of whether a public school, in a competitive market, will try to attract greater demand by enhancing its performance in order to keep in line with neighboring schools. This leads to our third hypothesis:

H3: As part of the strategic interaction among public schools, demand for a school is partially explained by neighboring schools' performance.

In that case, we complete the model by including neighbors' performance to see the impact of competition in performance on demand for places in a particular school. This scenario may break the "quiet life hypothesis" as a positive spatial spillover effect could be lower due to a higher performance of neighbors.

The proposed conceptual model, including the three above-mentioned hypotheses, is summarized in Figure 5.1.

Figure 5.1. The proposed conceptual model



From this review of the literature, sufficient arguments emerge in favor of competition in location and in performance between public schools (Hoxby, 2000a; Barrow and Rouse, 2004; Barrow, 2002; Millimet and Collier, 2008), but it is also evident the influence of competition from private schools in the academic performance of public schools, and vice-versa (Dee, 1998; Sandström and Bergström, 2005). Both aspects can be decisive in the choice of school made by parents. Given the lack of available data on private education institutions for the development of this thesis, we focus our analysis on public schools. To date, any previous paper has provided empirical evidence on how the demand for places in a public school behaves taking into account competition in location and in performance from other neighboring public schools. This is our main objective to be tested through hypothesis 1, 2 and 3.

Similarly, it would be interesting to examine whether or not the demand for a public school may also be affected due to the existence of neighboring private schools. In other words, whether or not there is strategic interaction among private and public schools. Despite not having data about private schools, we have further checked the literature about school choice to see if we can find preliminary evidence to answer this question. Many authors conclude that the drivers for school choice are different in private schools compared to public institutions (Fernández and Muñiz, 2012, and references therein). The first and the most important factor is families' socio-economic level. In fact, if family income level is high, parents do not consider the possibility of choosing a public school for their children, they select a private school. Likewise, when the average income level in the family is low, the priority is a public school. Mixed results could be obtained for families with medium-high income level, who doubt about whether they can pay a monthly fee for a private school or if they prefer a public school (Urquizu, 2008). In these specific cases, other factors play a role in the decision such as, the education project in the institution, the religious orientation (public schools in Spain are secular, while most private institutions are religious); the preference for a more elitist education, far from the multi-cultural reality of public schools; the school climate, the number extracurricular activities or the preference for languages. These factors would make parents to choose a private school over a public one.

Is this scenario, it should be noted that the quality of the education provided by each institution (private or public) is not included as a factor determining parents' choice. It appears that families with high income level prefer to pay for education (private school) if the probability of success (academic achievement) is greater than in public schools. Based on this premise, we wonder whether or not it is true that students attending private schools achieve better academic attainment than those attending public institutions. Does the academic achievement constiture a decision variable for parents?

The literature review concludes that students' academic achievement (as a proxy of the quality of the education provided) is not a significant factor in determining the choice of a private school over a public institution. A study conducted using PISA data (OECD, 2013) concludes that when the socio-economic level of families is not taken into account, students' achievement in private school is significantly better than those from public schools. This could help doubtful parents with medium-high income level to choose a private school over a public one. However, this study is convincing saying that when controlling for families' socio-economic level, differences in educational outcomes between private and public schools are not significant. Several empirical studies obtain similar conclusions, and even confirming that public schools perform better than private schools (e.g., Calero and Escardíbul, 2007; Mancebón and Muñiz, 2008; Calero and Wasgrais, 2009; Perelman and Santín, 2011a; Salinas and Santín, 2012). Therefore, the differences in academic results correspond almost entirely to the different socio-economic composition of the students.

After this review, and taking into account the objective of this chapter, we could advance that a priori, school choice decision made by parents may be affected not only by neighboring public schools, but also by the existence of private schools, as long as we are dealing with families who prioritize other factors unrelated to the academic achievement (due to the absence of significant differences between public and private institutions) as religious orientation, elitist education, extracurricular activities or preference for languages. However, the lack of data on private schools prevents us from conducting a deeply empirical analysis to test this proposition. We will consider this as an opportunity for further research in the future.

5.3 Methodology

To test the proposed hypotheses, we proceed in two stages. The first entails estimating school efficiency to obtain an objective measure for school performance (to proxy parents' perceptions about the quality of school management). The second step analyzes the spatial patterns of demand for places in schools and includes the efficiency score as an exploratory variable. We discuss each stage in turn.

5.3.1 Efficiency estimation

To proxy school's performance, we use a fully non-parametric efficiency estimation approach, the conditional and robust order-m model (Cazals *et al.,* 2002; Daraio and Simar, 2005, 2007a, 2007b) already introduced in Sections 3.3.2 and 3.3.3 of this thesis. To avoid repeating the same content about this model, here we just show the main features of this approach. Following with the basic notation used in this thesis, we consider a production process where schools are characterized by a set of inputs x ($x \in R_+^i$) and outputs y ($y \in R_+^k$). In this production process, environmental conditions (z) should be taken into account as they constitute a potential source of inefficiency as we demostrated in previous chapters ($z \in R_+^e$). In this framework, the joint distribution of (X, Y) conditional on $Z = z$ defines the production process if $Z = z$. Specifically, using a probabilistic formulation, the Farrell-Debreu measure of output-oriented conditional order-m efficiency score for a unit operating at the level $(x, y|\mathrm{z})$ is defined as:

$$\hat{\theta}_m\,(x, y|z) = \sup \theta|(x, \theta y) \in \Psi_m(x|z) = \sup\{\theta|\; S_Y(\theta y|x, z) > 0\} \qquad (5.1)$$

where $\Psi_m(x|z) = \{(x', y) \in \mathrm{R}_+^{i+k} \,|\, x' \leq x, z = Z, i = 1, \ldots, m\}$ and $S_Y(y|x, z) = Prob(Y \geq y|X \leq x, Z = z)$.

To estimate the conditional model, smoothing techniques are needed in *z.* At this purpose, the following kernel estimator of $S_Y\,(y|x, z)$ is used:

$$\hat{S}_{Y,n}(y|x, z) = \frac{\sum_{j=1}^{n} I(x_j \leq x, y_j \geq y) K_{\hat{h}}(z, z_j)}{\sum_{j=1}^{n} I(x_j \leq x) K_{\hat{h}}(z, z_j)} \qquad (5.2)$$

where $K_{\hat{h}}(\cdot)$ represents the kernel function, $I\,(\cdot)$ is an indicator function and h is an appropriate bandwidth parameter for this kernel. In that case, as in Chapters 3 and 4, we follow the data-driven selection approach developed by Badin *et al.* (2010) to select the bandwidth parameter h and a multivariate kernel function (De Witte and

Kortelainen, 2013) since we have mixed data in our data set. We employ the Epanechnikov kernel function ($K_{\hat{h}}(z, z_j) = h^{-1}K(\frac{z, z_j}{h})$) for continuous variables and the Li and Racine (2007) discrete kernel function for ordered variables. Finally, the conditional order-m estimator $\hat{\theta}_m(x, y|z)$ can be obtained by plugging in the new $\hat{S}_{Y,n}(y|x, z)$ in Eq. (5.1).

The efficient frontier corresponds to those points where $\hat{\theta}_{m,n}\ (x, y \mid z) = 1$. In this case the score can be lower than one. This would mean that the school is labeled as super-efficient, since the order-m frontier exhibits lower levels of outputs than the school being assessed.

5.3.2 The strategic interaction model

Our second research question concerns the effect of strategic interaction among public schools on parents' choice, that is, whether the demand for one school is partially affected by the competition in location and in performance. The intuition behind strategic interaction models is that policy makers do not make their decisions in isolation; rather, they react to the decisions made by other jurisdictions. As mentioned, public schools facing competition from other schools in the area might be concerned about the performance and level of demand for neighboring schools and might respond to the changes their neighbors adopt. As a standard feature in the literature on strategic interaction, our second-stage analysis is to estimate the spatial reaction function of the form:

$$D_j = \gamma + \rho D_n + \beta' R_j + \delta' C_j + \mu_j \tag{5.3}$$

where D_j is the level of demand for places in school *j*; D_n is the level of demand for places in neighboring schools; ρ is the strategic interaction parameter, as it represents the slope estimate of the spatial reaction function; R_j is a (r*p) matrix of explanatory variables (fully explained in Section 5.4.3); β' is a vector of parameters to be estimated for explanatory variables; C_j is a (c*p) matrix of control variables (explained below); δ' is a vector of parameters to be estimated for control variables; and μ_j is the corresponding error term vector. Eq. (5.3) let us test hypotheses 1 and 2 as it tests whether or not the level of demand for school j depends not only on its own performance and school characteristics (R_j) $(H1)$, but also on the level of demand for neighboring schools (D_n) $(H2)$.

Neighbors are determined by a number of standard criteria (weight matrices) that we discuss below. Every school has not one but multiple neighbors and this can be incorporated by replacing D_n in Eq. (5.3) with $\sum_{n=1}^{N} w_{j,n} D_j$ where $\sum_{n=1}^{N} w_{j,n}$ will take a non-zero value if school n is a neighbor of school j and zero otherwise. Each school is associated with a vector of weights that indicates the relative weight given to the demand for neighboring schools. Eq. (5.3) in an equivalent form is:

$$D_j = \gamma + \rho \sum_{n=1}^{N} w_{j,n} D_j + \beta' R_j + \delta' C_j + \mu_j \tag{5.4}$$

where $w_{j,n}$ is a $(n*n)$ weight matrix. The model given by Eq. (5.4) is commonly known as the spatial lag model or the spatial autocorrelation (SAR) model.

Finally, spatial dependence has been commonly treated as a phenomenon where neighbors' decisions have a multidirectional effect. Therefore, to test the third hypothesis about the effect of competition on performance, we should also include a spatial lag for explanatory variables (R), as given by Eq. (5.5):

$$D_j = \gamma + \rho \sum_{n=1}^{N} w_{j,n} D_j + \beta' R_j + \gamma' \sum_{n=1}^{N} w_{j,n} R_j + \delta' C_j + \mu_j \tag{5.5}$$

The model given by Eq. (5.5) is commonly known as the Durbin model, which also includes a spatial lag for explanatory variables. The empirical question of interest is whether ρ is significantly different from zero. Accordingly, testing for interdependence is, in this case, related to the parameter ρ, conditional on the respective weight matrix. The test of the null hypothesis that the reaction function's slope (ρ) is zero is effectively a test for the existence of strategic interaction. In addition, we are interested in knowing if the performance of neighboring schools impacts on the demand for the school under analysis. Therefore, the specific parameter γ' regarding the explanatory variable *performance* reveals the effect of this competitive force.

Before proceeding, several important points in the estimation of Eq. (5.5) merit discussion. The first question is the choice of the weights $w_{j,n}$. In general, it is difficult to define appropriate weights since there is no general criterion for discriminating between alternative definitions. W is a non-square stochastic matrix whose elements ($w_{j,n}$) reflect the intensity of the relationship between each pair of schools j and n. In the present study, we use a contacts matrix based on the inverse of the distance between two schools. Thus, the intensity of the interdependence between two schools decreases when the distance between them is higher. We consider this specification to be the best option to classify neighboring schools because, in normal circumstances, it is difficult to find two schools that are physically adjacent or that share a physical boundary.

Second, we must define what we mean by an education market. Earlier researchers have followed the traditional market structure theory to define the education market by assuming that it is bounded within a school district or county. These units of observation generally suffer from estimation issues such as aggregation bias (Birks, 2003). However, in reality a public school can face competition from other public schools within the district or from adjoining school districts in order to attract more students (and hence increase demand). By redefining the market at the school level, this study will provide better and more precise information about competition on public school performance and demand.

A third point is the potential presence of spatial error correlation due to some unobserved characteristics of a school that tend to be correlated for neighboring schools. For example, public schools may be exposed to common issues: changes in taxes or in state government policies. Hence, accounting for the potential presence of spatially correlated components in the errors is crucial; otherwise we may incorrectly conclude that strategic behavior is evident. In this study, spatial error correlation is taken into account. The approach takes the example of unobserved region-specific effects and includes in Eq. (5.5) a number of dummy variables for REAs as control variables (C_j). Of course, for the approach to make sense these areas have to be meaningfully defined. In the education system in Catalonia, the natural way to proceed is to define REAs according to the scope of action of the Inspectors of

Education from the Department of Education. These REAs act as local agencies in each area of Catalonia. The dummy variables will take account of any such region-specific effect on school demand, thereby helping remove spatial correlation from the errors.

For robustness, Lagrange Multiplier (*LM*) tests (Pinkse and Slade, 1998) are applied to circumvent this problem. The results of these tests are used to identify the exact source of dependence among school inputs (Anselin, 1988). Running the test on generalized residuals from a standard OLS model and a model including the dummies will reveal the extent to which including these dummies removes spatially correlated components from the residuals (these results are shown in Section 5.5).

5.4 Data and Variables

The data for this study come from the Evaluation Council of the Education System in Catalonia, the institution in charge of conducting the basic skill tests in this region. As in the rest of the thesis, the relevant unit of observation is the school, as we stated in our definition of the education market in the Section 5.1. To perform this analysis, we have data on 364,771 students and 1,127 schools[15] for the academic year 2009-10, distributed across ten REAs as shown in Table 5.1.

Table 5.1. Distribution of students and schools by REA

REA	Number of schools	Number of students
A1. Baix Llobregat	147	49,906
A2. Barcelona comarques	125	41,422
A3. Catalunya central	70	21,677
A4. Consorci d'Educació de Barcelona	167	49,203
A5. Girona	109	37,091
A6. Lleida	64	15,641
A7. Maresme	162	51,692
A8. Tarragona	98	32,844
A9. Terres del Ebre	28	9,521
A10. Vallès Occidental	157	55,774
Catalonia	**1,127**	**364,771**

[15] It is worth noting that in this chapter we are considering schools located in urban municipalities, as stated earlier in Section 5.1. This fact reduces our sample of schools from 1,694 to 1,127.

5.4.1 Variables for efficiency analysis

To focus the analysis, we first present the variables used in the efficiency estimation (Table 5.2). As can be seen, we are using the same variables we presented before in Sections 3.4.2 and 4.3. Indeed, we preserve the same efficiency model in this thesis. The difference in that case is the consideration of outputs. Instead of using the average grade in all tests, here we are including information about the average grade in Languages and Mathematics due to the fact that we achieved more information from the Evaluation Council of the Education System.

Table 5.2. Description of variables for efficiency analysis

Category	Variable		Description
Inputs	X_1	Teachers	Total number of teachers working at the school.
	X_2	OPEX	School operational expenses in the academic year.
Outputs	Y_1	Languages	Average mark in languages (average of Spanish, Catalan and English tests) in the general sixth grade test.
	Y_2	Mathematics	Average mark in mathematics in the general sixth grade test.
	Y_3	Passed	Number of students who pass the tests.
Environmental factors	Z_1	SES	Families' socio-economic status. 1. Other workers. 2. Middle managers. 3. Technicians. 4. General managers. 5. Entrepreneurs.
	Z_2	Unemployed	Percentage of unemployed parents.
	Z_3	Immigrants	Percentage of non-Spanish students.
	Z_4	Annual absenteeism	Percentage of student absences during the academic year (students absent more than 75% of all days).
	Z_5	Educational needs	Percentage of students with special educational needs (autism, personality disorder behavior, psychological, motor, auditory or visual impairment, Down's Syndrome, exceptionally gifted).
	Z_6	Late incorporation	Percentage of newly incorporated students (halfway through the year).
	Z_7	Teachers mobility	Percentage of teacher turnover (newly incorporated teachers plus those who leave the school).

Table 5.3 reports the main descriptive statistics of inputs, outputs and environmental variables. As can be seen, urban schools employ, on average, 26.047 teachers, including both permanent and non-permanent teachers. The smallest school has only two teachers whereas the biggest one has 52. The mean *OPEX* is €8,961.546, although the maximum rises to €63,265.625. On average, parents have a technical profession. In terms of outcomes, not all the students pass the aptitude test: we find grades below

50 out of 100 in both languages and Mathematics tests. The average grade in these subjects is 65.144 and 72.515 points, respectively. Finally, our sample is characterized by a relatively high percentage of unemployed parents, 16.776%; immigrants, 14.195%; and teacher mobility, 25.174%, on average. The absenteeism rate is also considerable, despite the fact that we are dealing with primary education.

Table 5.3. Descriptive statistics for efficiency variables

Variable	N	Min	Q25	Mean	S.D.	Median	Q75	Max
X_1	1,127	2.000	19.000	26.047	9.234	29.000	33.000	52.000
X_2	1,127	2,266.123	5,958.557	8,961.546	3,748.957	9,022.684	10,750.855	63,265.625
Y_1	1,127	30.403	58.732	65.144	10.524	67.331	72.874	93.034
Y_2	1,127	35.904	66.468	72.515	9.909	74.251	80.254	97.590
Y_3	1,127	6.000	169.500	273.250	133.226	264.000	388.000	685.000
Z_1	1,127	1.000	1.528	2.580	0.352	2.593	2.828	5.000
Z_2	1,127	3.000	11.020	16.776	7.862	13.935	20.879	52.852
Z_3	1,127	0.000	5.683	14.195	11.987	10.644	19.456	74.262
Z_4	1,127	0.000	0.000	1.175	2.653	0.222	1.108	23.762
Z_5	1,127	0.000	0.281	1.821	2.383	1.142	2.375	28.000
Z_6	1,127	0.000	0.000	1.873	4.273	0.411	2.378	90.000
Z_7	1,127	0.000	14.960	25.174	15.629	23.530	33.333	100.000

Table 5.4 presents the correlation matrix among efficiency variables. As in previous chapters, both the tolerance and VIF tests show values that give no cause for concern. In all the cases tolerance is higher than 0.3 and VIF is lower than 3 (see Belsley *et al.,* 1980 for thresholds).

5.4.2 Variables for the strategic interaction model

We use the same dataset to run the spatial regression model to better explain the behavior of demand for places in public schools. The empirical analysis is conducted in public schools located in urban municipalities, as they are facing competition in performance to attract more students and encourage demand from parents. Table 5.5 summarizes the variables.

Table 5.4. Correlation matrix between efficiency variables

	X_1	X_2	Y_1	Y_2	Y_3	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7
X_1	1											
X_2	0.659**	1										
Y_1	0.416***	0.636***	1									
Y_2	0.424***	0.658***	0.902***	1								
Y_3	0.874***	0.577***	0.437***	0.428***	1							
Z_1	-0.012	-0.032	0.354**	0.321**	0.217**	1						
Z_2	0.028	0.104	0.125*	0.122*	0.113*	-0.485***	1					
Z_3	0.014	0.050*	-0.249**	-0.232**	-0.233**	-0.524***	0.282***	1				
Z_4	-0.052*	0.083**	-0.192**	-0.178**	-0.120**	-0.223***	0.097**	0.195**	1			
Z_5	0.026	0.060**	-0.065*	-0.052*	-0.020	-0.073*	0.042	0.032	0.185***	1		
Z_6	0.076**	0.024	-0.184**	-0.171**	-0.150**	-0.164**	0.096***	0.338***	0.101***	0.087**	1	
Z_7	-0.121**	-0.063**	-0.378**	-0.369**	-0.179**	-0.023	0.104***	0.041	0.060	0.034*	0.119**	1

Notes: ***, **, and *: Below the 1%, 5% and 10% statistical significance thresholds, respectively.

The dependent variable we want to explain is demand for places in the school (*demand)*. This is a ratio between the number of enrollment applications from families (their first option in the enrollment application) and the places offered by the school. This is a non-negative variable. A ratio equal to one indicates that the places offered are fully covered by demand from parents. When the coefficient takes a value less than one, not all places are covered, reflecting lower demand for this school. Conversely, a value higher than one indicates that the demand for this school is higher than the supply, and thus that it is perceived by parents as a high-performance school.

Table 5.5. Description of variables for the strategic interaction model

Category	Variable		Description
Dependent variable	D	Demand	School demand defined as the ratio of enrollment applications from parents over the places offered by the school.
Exploratory variables	R_1	Performance	Inverse of efficiency score obtained from the conditional order-*m* estimation. It reflects the school's performance after controlling for environmental variables.
	R_2	*TIP*	Teaching innovation projects. Binary variable reflecting whether or not the school was awarded recognition for innovation projects, as part of its teaching curriculum.
Control variables	C_1	School age population	Percentage of school age inhabitants (younger than 16 years old) in the municipality.
	C_2	REA	Specific educational area within the public education network in Catalonia (A1 to A10).

Two measures regarding school characteristics are included as explanatory variables (*Performance* and *TIP)*. Firstly, we include the inverse of efficiency score[16] as a proxy for quality of school management. Secondly, we include information about the availability of teaching innovation projects (TIP) at the school. Innovation projects include the introduction of new methods of teaching and learning. The literature on innovation in education is sparse. In recent decades, much of the discussion of innovation has focused on the use of audio-visual aids, and educational, communication and information technology. Underlying most of the general discussions are unquestioned assumptions about what constitutes innovation in

[16] As we run an output-orientation efficiency model, the score goes from 1 to infinite, where a score equal to 1 means the unit is efficient. Hence, it is an inefficiency more than an efficiency score. To avoid possible confusions, we calculate the inverse of this efficiency score, and include it as a regressor.

education. Hannan *et al.* (1999) conclude that education institutions implement TIP for different reasons: to improve students' learning, to respond to changes in student intake, to address the demands of external agencies and to adapt their methods of teaching and learning to cope with curriculum change or internal reorganization. Schools working with TIP give out a sign of excellence in performance that parents can appreciate and value when selecting a school.

Finally, we include two control variables (*school age population* and *REA)*. As we explained in Section 5.3.2, we include area dummies reflecting regional educational areas in Catalonia to control for autocorrelation in the error term. In addition, we include the percentage of school age population to control for municipality size.

Table 5.6 presents the main descriptive statistics of these variables and Table 5.7 the correlation matrix.

Table 5.6. Descriptive statistics for regression variables

Variable	Continuous Variables	N	Min	Q25	Mean	S.D.	Median	Q75	Max
D	Demand	1,127	0.01	0.620	0.825	0.455	0.888	1.080	4.000
R_1	Performance	1,127	0.871	0.940	1.141	0.316	1.009	1.132	1.870
C_1	School age population	1,127	12.365	15.366	16.462	2.274	16.551	17.792	23.363
Variable	**Nominal variables**	**N**	**Min**	**Percentage**	**Max**				
R_2	TIP (0: No, 1: Yes)	1,127	0	0.5359	1				
C_2	A1			0.1304					
	A2			0.1109					
	A3			0.0621					
	A4			0.1482					
	A5			0.0967					
	A6			0.0568					
	A7			0.1438					
	A8			0.0869					
	A9			0.0248					
	A10			0.1393					

As can be seen from Table 5.6, on average schools do not fill all their available places, indicating that they have the capacity to take more students, which translates in improvement possibilities to attract new students and therefore greater demand from parents.

Regarding school performance, we can confirm that the average conditional efficiency score is 1.141 (*performance* in Table 5.6). This means that in our sample schools can perform better if they mimicked the best practice schools. The number of students who pass the course and their academic results in languages and Mathematics tests could increase by an average of 14.1%. It is important to note that our sample has some super-efficient schools that are performing better than the average *m*[17] schools they were benchmarked against.

Table 5.7. Correlation matrix for regression variables

	D	R_1	R_2	C_1	C_2
D	1				
R_1	0.621**	1			
R_2	0.268**	0.026**	1		
C_1	0.014**	-0.059**	-0.102	1	
C_2	-0.131***	0.048	0.007	0.298***	1

Notes: ***, **, and *: Below the 1%, 5% and 10% statistical significance thresholds, respectively.

5.5 Results and Discussion

5.5.1 Preliminary evidence of spatial dependence

The main goal of this chapter is to test whether there is strategic interaction in parents' selection for a school when increasing choices are available. As previously mentioned, we apply spatial econometrics techniques (Anselin, 1988; LeSage and Pace, 2009). Exploratory spatial data analysis (ESDA) enables us to identify different patterns of spatial association and regional clusters or atypical locations, which is particularly important to gain a view of the demand for schools in Catalonia. Our empirical analysis begins with an initial picture of the distribution of demand for schools in Catalonia, presented in Figure 5.2.

[17] Following Daraio and Simar (2005, 2007a, 2007b) we use value of m for which the decrease in super-efficient observations stabilizes. We therefore fix m = 140. For bootstrapping we fix B=200

Figure 5.2. Spatial distribution of school demand in Catalonia

The figure reveals disparities in the proportion of demand across Catalonia. Specifically, two different conclusions can be drawn from this chart. First, while demand for schools located in the most remote municipalities is low, the highest values are concentrated in cities or central regions. The first group includes the more distant cities of *Lleida* and *Tarragona*, which present lower values compared to the city centers of *Barcelona* and *Girona* where the demand for schools is higher. Second, demand does not seem to be randomly distributed across space. We can observe a positive spatial association between adjacent areas because they show similar values of demand for schools.

Some caution is recommended when interpreting the data from Figure 5.2, since the conclusions that might be drawn are highly sensitive to the number and width of the different intervals used to represent the variable of interest. Additional analysis should be performed to determine the degree of spatial interdependence between the values of the variable of study at different geographic locations. For this reason, we supplemented the preliminary evidence provided by Figure 5.2 with a formal analysis of the possible presence of spatial autocorrelation in our data using Moran's I test (Moran, 1948). The Moran *I*-statistic is a measure of similarity between association in value (correlation) and association in space (proximity) and is widely used in detecting spatial dependence in data (Cliff and Ord, 1981). If the Moran *I*-statistic is positive and significant a positive spatial autocorrelation exists, therefore similar values of the dependent variables are spatially clustered. Conversely, a negative and significant Moran *I*-statistic indicates that there is no spatial clustering.

Table 5.8 reports Moran's I test results for spatial dependence in the dependent variable, demand for the school, using the weight matrix w_{jn} based on the inverse of the distance between schools.

Table 5.8. Tests to detect spatial dependence

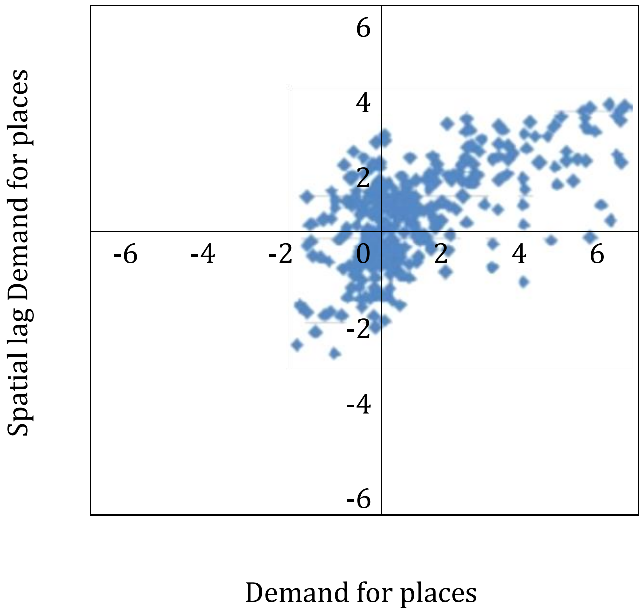
	Coefficient	p-value
Global tests		
Moran's I	0.9616	0.003***
Lagrange multiplier tests		
LM ERR	0.2064	0.649
LM LAG	0.9142	0.039**
RLM ERR	2.1122	0.146
RLM LAG	2.8201	0.023**
SARMA	2.8265	0.020**

Notes: ***, **, and *: Below the 1%, 5% and 10% statistical significance thresholds, respectively.

As can be seen, there is evidence of spatial clustering for demand in our data. The positive and significant value of Moran's I (0.9616, *p*-value = 0.003) signals that demand for neighboring schools is similar (either high or low), and hence spatial clustering is present. This is evidence of a pattern of positive spatial association in this context, which is consistent with the initial impression drawn from Figure 5.2. We can conclude that, on the whole, schools located in spatially adjacent zones tend to share similar levels of demand.

To further confirm this finding, we also present the corresponding Moran's scatterplot (Figure 5.3) for the distribution of demand for places in public schools in Catalonia. As can be seen from Figure 5.3, the majority of the schools considered are located in quadrants I and III. This confirms that Catalonia is characterized by the presence of spatial clusters of schools with similar levels of demand while there are relatively few cases in which a zone registers a value of the analyzed variable that is markedly different from the average of its neighbors.

Figure 5.3. Moran's *Scatterplot*



Preliminary exploration of the data using Moran's I test results provide some evidence of a spatial pattern in the data, suggesting that it is necessary to include spatial effects instead of relying on the non-spatial OLS model. However, Moran's test alone is unable to establish which kind of spatial dependence is present in our data.

A more precise indication of the most likely source of spatial dependence is given by the two Lagrange Multiplier (LM) tests (see Anselin, 1988, 2006). These are the LM ERR and LM Lag and their robust versions, RLM Error and RLM Lag, which are designed to test for the spatial error/substantive autocorrelation, respectively. The results of the robust LM tests are reported in the lower section of Table 5.8. The results lead to the rejection of the null hypothesis of absence of substantive spatial dependence as LM LAG and its robust version are significant at the 95% confidence level. However, we cannot reject the null hypothesis of absence of spatial error autocorrelation as LM ERR and its robust version are not significant. Indeed, the values of the Lagrange multiplier tests calculated suggest that in this context the spatial lag model (SAR) is preferable to the spatial error model (SEM). Therefore, we can conclude that first, the demand for a school in an area *j* is affected systematically by the demand for schools in neighboring areas *n*; and second, there are interdependencies in the demand among schools located in neighboring areas due to, among other factors, spillover effects between neighboring areas.

5.5.2 Spatial regression results

To correctly introduce the impact of spatial dependence detected, the next step is to run the spatial models. In this case, we use the Maximum-Likelihood approach as we do not have significant endogeneity problems (explained below in Section 5.5.3). As can be seen from Table 5.9, we first develop two OLS models to further check for spatial error autocorrelation (Model 0 and Model 1). Then, a spatial autoregressive structure is included first in the dependent variable (Model 2 - SAR), which corresponds to Eq. (5.4). Finally, we contrast the model by adding a spatial autoregressive structure in the explanatory variables (Model 3 - DURBIN) which matches Eq. (5.5).

The first step in the analysis is to run two baseline regressions where the potential impact of neighbors' lagged policies is ignored (Model 0 and Model 1). The baseline regressions will help us to address the issue of spatially correlated unobserved effects. Table 5.9 reports these results. As mentioned in Section 5.3.2, controlling for region-specific effects is a straightforward way of removing spatially correlated components from the residuals. To see how this approach works in the present setting, a LM test for spatial error correlation was performed for two OLS specifications (one with REA dummies and one without them). As suggested by Pinkse and Slade (1998), a bootstrapping method is used to derive *p*-values for the null hypothesis of zero spatial error correlation.

The results are reported in the last row in Table 5.9. The result for the model without REA dummies (Model 0) clearly suggests the rejection of the null hypothesis of zero spatial correlation in errors. In contrast to this, once region-specific dummies are included (Model 1), the *p*-value of the test reveals that there is no significant amount of spatial error correlation. Therefore, when moving to specifications with spatial interaction, there is no reason to suspect that the results will be significantly affected by spatially correlated unobserved effects once the impact of *REA*s on district policies is accounted for.

Table 5.9. Spatial regression results

	BASELINE OLS MODELS		SPATIAL MODELS	
	Model 0	**Model 1**	**Model 2**	**Model 3**
Variable/Model	**OLS**	**OLS**	**SAR**	**DURBIN**
Intercept	0.7556***	0.6182***	0.5564**	0.7836***
	(0.1497)	(0.1621)	(0.2229)	(0.5215)
Performance	0.0729**	0.0954**	0.0995**	0.1004**
	(0.1002)	(0.1010)	(0.1006)	(0.1007)
TIP	0.0623*	0.0599*	0.0602**	0.0689**
	(0.0272)	(0.0272)	(0.0270)	(0.0271)
School age	0.0745*	0.0764*	0.0352*	0.0657*
population	(0.0596)	(0.0402)	(0.0089)	(0.0093)
REA dummies	*No*	*Yes*	*Yes*	*Yes*
Lag Demand			0.7782**	0.6628*
			(0.1948)	(0.3077)
Lag Performance				-5.1986*
				(2.5533)
Lag TIP				-0.5489*
				(0.3854)
LN L			-692.6606	-676.4545
AIC			1406.9	1413.3
***p*-value LM test for residual autocorrelation**	0.0382**	0.1460	0.1802	0.1605

Notes: (1) The dependent variable is the school demand. (2) Robust errors in parentheses. (3) Matrix type: inverse of distance matrix. (4) ***, **, and *: Below the 1%, 5% and 10% statistical significance thresholds, respectively.

In both models the coefficient of explanatory variables *performance* and *TIP* is positive and significant at the 5% and 10% levels, respectively. These results suggest that schools with a higher performance level and with TIP attract greater demand from parents. These results confirm *H1*. Hence, we can confirm *H1* at the 5% level and conclude that, in an environment of increasing choices, parents do take into account the quality of school management when choosing a public school for their children. As parents do not have access to any official indicators about schools in Catalonia, they decide on a particular school based on personal judgments about the quality of management and this perception resembles efficiency score.

These models do not include the role of competition in location to test *H2* and in performance to test *H3*. To do so we should run the spatial models from Eq. (5.4) and Eq. (5.5). We now turn to estimates of the spatial models, where the focus is on identifying the impact of demand and performance for neighboring schools due to strategic interaction. The second set of results in Table 5.9 corresponds to two spatial models (SAR and DURBIN). Note that, as suggested by the results of the tests reported above, a full set of REAs dummies is included to remove spatially correlated components from the errors. In addition, it is worth noting that the estimated coefficients on neighboring values should be interpreted as elasticities since we model the variables in their natural logarithmic form.

To test *H2*, we move to Model 2, which includes a spatial lag of the dependent variable. The focus is now on the strategic interaction parameter ρ in Eq. (5.4). This parameter is of interest because it indicates the importance of spatial interactions in the demand for places in public schools. The positive and significant estimate of ρ (*Lag Demand*) in Model 2 of Table 5.9 shows that a 1% increase (decrease) in the demand for neighboring schools increases (decreases) the demand for the school under analysis by 0.7782%. This implies a positive neighborhood influence in demand levels; that is, they behave as strategic complements. These results are consistent with some degree of interdependence in neighboring DMUs, corroborating previous findings in strategic interaction studies, as summarized in Section 5.2. Explanatory variables show coefficients that are significant at the conventional levels and the signs are consistent with prior expectations. Again, the higher the school's performance, the higher the demand from parents.

Results from Model 2 confirm *H2* at the 5% level and reinforce *H1* when including the role of competition in location. Hence, there is strategic interaction in the demand for public schools. In fact, the demand for one school is not only explained by its performance (quality of management), but also by the demand for its neighboring schools. As Barrow (2002) states, parents decide on a particular public school through location choice. The main implication of this finding is that, even without taking into account private schools, public schools already face some competition from other public schools in the area and this fact impacts on parents' choice.

We now turn to Model 3 to test *H3*. In that case, our focus is not only on ρ (*Lag Demand*) but also on the spatial lag of performance, included in γ' in Eq. (5.5) (*Lag Performance*). In other words, we want to test if the performance of neighboring schools impacts on the demand for the school under analysis. If this is the case it would reinforce the existence of competition between public schools. The results confirm our intuition as, despite maintaining the positive and significant spatial spillover effect from demand for neighboring schools (*Lag Demand* = 0.6628*), public schools should not neglect their performance. Indeed, neighboring schools' performance negatively impacts on the demand for the analyzed school at the 10% level. Specifically, a 1% increase (decrease) in their performance decreases (increases) the demand for the school under analysis by 5.1986%. In other words, public schools do appear to be under a significant amount of competitive pressure from neighboring public schools.

As can be seen from last column in Table 5.9, the coefficient for the autoregressive parameter ρ is slightly lower and less significant than the same parameter in Model 2 (*Lag Demand* = 0.7782** in Model 2 and 0.6628* in Model 3). This finding, together with the coefficient of *lag performance,* confirms *H3* at the 10% level, proving that there is strategic interaction in demand for public schools. In fact, the demand for one school is not only explained by its own performance in management, but also by the demand and performance in neighboring schools.

As we stated in the introduction of this chapter, the public education system is not devoid of competition (Hoxby, 2000a; Barrow and Rouse, 2004; Millimet and Collier, 2008). Public schools have to compete with other nearby public schools and enact strategies that will help retain as well as attract more students. Chubb and Moe (1990) asserted that school leaders respond to market pressures because they "*have a strong incentive to please a clientele of parents and students through the decisions they make*" (p. 32). Millimet and Rangaprasad (2007) argue that this is an alternative, complementary approach to analyze the impact of competition arising from other public schools. Indeed, understanding the strength of the competitive forces emanating from alternative public schools may also shed light on the value added by additional competition that may be induced through expanded school choice.

In summary, in an environment of increasing choices for parents, demand for places in a particular public school depends on its own performance (quality of management), and the demand and performance of neighboring public schools. The positive and statistically significant estimates in *lag demand* in Models 2 and 3 indicate that the reaction function is upward sloping and suggests evidence of strategic dependence in school demand. However, this positive spatial spillover effect diminishes when we include the performance of neighbors (*Lag Performance*) indicating that public schools already face competition in performance to attract students.

5.5.3 Robustness analysis

Before closing this analysis, we should explain some points regarding the estimations. We performed several additional tests to check for robustness in the results.

The first question refers to the validity of the model. We are interested in testing the implicit hypothesis that using a variable obtained from a sampling technique as a regressor can induce invalid inference. To do so, we run two non-parametric efficiency estimations; the first involves applying a sampling technique, order-*m* model, and the second is a full frontier estimation, FDH. We then run a structural difference test (*F*-test) comparing the regression coefficients of the two variables (H_0: *FHD estimation – order-m estimation = 0*). The result from the test does not allow us to reject H_0 (*F-statistic = 1.08, p-value = 0.2998*). Therefore, we can confirm that there are no significant differences in the regression coefficients obtained from the two efficiency estimations. As we stated in Section 5.3.1, order-*m* estimations are more robust to the presence of atypical observations or noise in the data than full frontier models such as FDH. For this reason, we use an order-*m* model to proxy the performance of public schools. In addition, we apply a conditional approach to introduce the effect of environmental variables in the efficiency score. By using a conditional model we avoid the restrictive separability assumption required by traditional approaches in order to provide meaningful results.

A second subject is the definition of the observable variable. As we stated in the introduction of this chapter, we are concerned about parents' perceptions when selecting a school for their children. In Catalonia, parents can choose up to 10 public schools based on their personal judgments about the quality of school management and the area where it is located. The lack of official information about academic performance by students, raises the question of how to proxy parents' perceptions. Do they really perceive school performance (as a proxy of quality of management), or do they select a school based on its previous knowledge about academic achievement? In other words, we aim to test whether demand for a school is higher because parents perceive it as efficient (as a proxy of quality of management) or whether they are simply guided by the colloquial information on students' achievement in previous academic years. To do so we use Wald's test (Wald, 1947) to establish which variable better explains the demand for a school. The null hypothesis here is that the two variables (grades and efficiency) are statically equal and explain demand for a school to the same degree. The result of the test allows us to reject the null hypothesis at the 95% confidence level (*H_0: grades - efficiency score = 0, F-statistic = 4.32, p-value = 0.0134*). Thus, the two variables do not explain demand for a school to the same degree.

In order to determine which variable better explains the demand for a school, we run a regression model using demand as the dependent variable and including both variables (grades and efficiency) as explanatory variables together with control variables (C_1 and C_2). The regression results confirm that students' grades do not significantly impact the demand ($coefficient$ = 0.0392, *p-value* = 0.723), while there is a positive and significant relationship between the efficiency score and the demand for the school ($coefficient$ = 0.0626, *p-value* = 0.050). Therefore, we can conclude that the model works better when we include the efficiency score as the explanatory variable rather than students' grades. To some extent, parents perceive the quality of school management and this appreciation corresponds better to the efficiency score.

A further point concerns the direction of the relationship between efficiency and school demand. In this case we want to know whether demand for a school is higher because is more efficient or whether, on the contrary, it is more efficient due to this higher demand. In other words, we have to test the causality between these two variables taking into account the spatial component of the data. Testing for causality is not simple, and the difficulties are compounded in a spatial cross-section environment where the relationships are simultaneous. In this case we apply a non-parametric test that allows us to detect spatial causality in cross-sectional data developed by Herrera *et al.* (2014)[18]. This new test for causality in pure cross-sectional spatial data is based on the Granger-Wiener approach (Wiener, 1956; Granger, 1969). It tests the null hypothesis of non-causality (*H_0: x does not cause y under a spatial structure*). In our case, we test the *H_0: efficiency does not cause demand for a school under a spatial structure*. The test results show that spatial causality runs from efficiency to demand (*coefficient* = 0.0028, *p-value* = 0.0025), but not from demand to efficiency (*coefficient* = 0.0136, *p-value* = 0.4700). Indeed, there is a sign of causality in our data set in the sense that the information flow is unidirectional from efficiency to school demand. Therefore, space is relevant in interpreting the relationship between efficiency and demand as these two variables are not spatially independent.

The last point involves testing for endogeneity in the efficiency score. As a random variable, this regressor might be correlated with the error term. This particular source of endogeneity is common in deterministic models. Although measurement errors can shift the frontier, they are largely neglected (Greene, 2005). In the case of measurement errors, the efficiency scores will be biased due to the increased variability. Some suggested methodologies such as order-*m* or order-*alpha* mitigate the influence of measurement errors by resampling the original sample. As well as applying a robust order-*m* estimation, we also performed a *t*-test between the efficiency score and the errors after running the spatial Durbin model from Eq. (5.6). In this case the *H_0 is: true correlation is equal to 0.* The test result confirms that we do not have significant endogeneity problems (*p-value* = 0.3911).

5.6 Conclusions

School choice reforms have been promoted with the objective of improving school performance through increased competition. The literature assessing the relationship

[18] See the paper by Herrera et al. (2014) for a detailed explanation of the test.

between standard measures of school performance and efficiency is extensive. However, little has been written about the mechanisms explaining parents' choice of public schools and how their decision affects school performance. Recent proposals call for expanded school choice programs to raise competition in public education. Thus, market-based reforms may be an ideal solution to increase the overall quality of public school education. However, we know little about how public schools and parents behave when competition increases due to more open school choice policies.

To contribute to this important policy debate, the main goal of this chapter has been to analyze whether there is strategic interaction in parents' selection for a school when increasing choices are available. We assess the extent to which performance and demand in neighboring competing public schools have a positive spillover on demand for places in a particular school. This question is crucial in formulating incentive structures that will efficiently reap the benefits of competition in demand for a school.

This study attempts to address this main goal through a specific approach that differs from the previous literature in three major aspects. First, this is the first study that analyzes the role of geographic location and competition in explaining the distribution of demand for a school in the Spanish context. Second, from a methodological perspective, unlike previous analysis in the economics of education literature, our study applies a robust efficiency model together with spatial econometric techniques that allow us to capture the spatial characteristics of the data and the influence of geographic proximity in shaping demand for places in public schools from Catalonia. This approach is particularly useful in the regional context as spatial econometrics has become such a prominent topic in the recent related literature. Third, the analysis in this study has focused on the school level as the unit of analysis for the education market. Previous research in education lacks a proper definition of a school market because many authors have used the district level (Misra *et al.,* 2012).

Our sample consists of 1,127 public primary schools located in urban municipalities in Catalonia. The findings support the idea that competition matters and reveal important differences in demand for schools across Catalonia. Increased demand for neighboring schools leads to higher demand for the analyzed school. Therefore, the empirical evidence reveals the presence of positive spatial autocorrelation. This implies that demand for schools is not randomly distributed across space. Indeed on the whole, a similar demand tends to be seen in physically adjacent zones as reflected in our study, which detected several clusters of schools with similar demand values. That said, it does not immediately follow that new sources of competition will have similar positive effects, as the performance of neighboring schools has diminishing effects on the demand for a school.

We carried out a causal analysis of the observed regional differences. Bearing in mind the consequences of ignoring the presence of spatial dependence, we estimated a model incorporating a spatial autoregressive structure in the dependent variable (SAR model) and in the explanatory variables (DURBIN model). It is important to note here that, as far as we are aware, this is the first study that uses a spatial model together with robust efficiency analysis to explain the behavior of demand for places in public schools in the Spanish setting.

Our results indicate that the more efficient a school is, the greater the demand from parents, thus confirming *H1*. In addition, the results obtained clearly show the importance of location in explaining the regional distribution of demand for a school. The empirical evidence also indicates that the transmission of spatial spillover effects across schools in neighboring areas is relevant. This means that the location of the school is an important factor in parents' decisions and this affects the demand for it. In addition, demand for a school depends on the demand for its neighbors as they compete to attract more students. These findings confirm *H2*.

When the role of competition is included in the analysis, our results confirm that there exists competition in performance among public schools in Catalonia (thus, confirming *H3*). As parents perceive how the school performs, they can better decide the most suitable school for their children by taking into account not only the distance from their residence, but also the quality of management. This fact confirms the presence of a competitive structure in the public education market that forces schools to perform as well as they can in order to maintain high demand and to justify their budget to the Department of Education.

These results might have significant implications. First, they provide valuable information for public decision makers facilitating the implementation of improvement programs in schools for which demand is lower. Thus, it seems likely that there is room for relatively new policy initiatives to yield further increases in demand. These policies can contribute to raising school quality, motivation, and competition within the system. In this context, the magnitude of territorial imbalances in the demand for schools should encourage policy makers to increase efforts to reduce the existing differences among areas. Second, by taking into account the relevance of spatial issues in this setting, a selective policy to encourage schools to adopt innovative teaching plans should be developed at a regional level. Thus, an active school quality policy put into practice in a specific neighborhood not only affects the number of schools in that area, but might also influence the demand for schools in adjacent zones. This may provide other schools in the area with valuable information concerning, for instance, the behavior of parents and students and administrative procedures.

Despite these implications, and apart from the lack of data from private schools highlighted in Section 5.2, the study has a limitiation concerning location, since we use schools' location instead of students' residence. Information about the place of residence for students could lead to a better estimation on whether parents choose the nearest school or if they really choose the one they consider the best for their children. Unfortunately, the lack of information about the exact location of each student prevents us from conducting this analysis. In fact, we are aware that the place of residence can be modified by parents in order to get access to a better school, despite the fact that this school is not in the neighboring area.

So far, the empirical analysis applied in this thesis has been cross-section, i.e., a static analysis of technical efficiency through the application of different methodologies to give answer to several research objectives. However, everything has been done in a particular academic year (i.e. 2009/2010). As we stated in the introduction of this thesis and in Section 4.5, the last step to close the empirical analysis of the thesis entails conducting a longitudinal analysis in which one can observe the evolution of schools' efficiency and productivity over time.

This objective is developed in the last empirical chapter of the thesis, Chapter 6. The main goal is to examine the effectiveness and efficiency of a program to improve educational quality in public primary schools from Catalonia. To do this, not only are the evolution of management efficiency and productivity analyzed, but an impact analysis is also carried out of the effectiveness in implementing the program.

CHAPTER 6.

QUALITY IMPROVEMENT PROGRAMS IN PUBLIC SCHOOLS. AN EVALUATION OF THEIR EFFECTIVENESS AND EFFICIENCY

6. QUALITY IMPROVEMENT PROGRAMS IN PUBLIC SCHOOLS. AN EVALUATION OF THEIR EFFECTIVENESS AND EFFICIENCY

6.1 Introduction

A central question in economics of education is how to increase the quality of education provided by public schools (Caputo and Rastelli, 2014). From the policy makers' point of view, many OECD countries are applying new school reforms which aim to improve students' academic achievement (OECD, 2011; 2013). From the research side, empirical evidence on the effectiveness of implementing such educational policies is becoming essential (Meghir and Palme, 2005). However, providing this evidence is not an easy task, as it requires the application of specific research methods to derive the causal impact of a program or a policy initiative on the treated population (Schlotter *et al.,* 2011).

Previous empirical studies have applied different impact evaluation research methods to assess the effect on educational outcomes of several school reforms[19], including the increase in instructional time or compulsory schooling time (Meghir and Palme, 2005; Black *et al.,* 2008; Bellei, 2009; Pekkarinen *et al.,* 2009), the introduction of vouchers (Peterson *et al.,* 2003; Angrist *et al.,* 2006; West and Peterson, 2006; Correa *et al.,* 2014), the application of year-round school calendars (Graves, 2011), the provision of extra funding or technical assistance to schools with a high proportion of disadvantaged students (Leuven *et al.,* 2007; Ludwig and Miller, 2007; Bénabou *et al.,* 2009), the introduction of accountability policies (Hanushek and Raymond, 2004; Jacob, 2005) or teaching innovation policies in schools (Machin and McNally, 2008), and even the elimination of a student aid program (Dynarski, 2003).

However, none of them include the crucial dimension of quality of education. Previous empirical research has shown that public policies aiming to improve

[19] See the papers by Schlotter *et al.* (2011) and Webbink (2005) for a detailed literature review.

students' outcomes and quality in education could help politicians make effective and efficient policy decisions about how to allocate money to education (Hummel-Rossi and Ashdown, 2002). Indeed, quality of education improves the quality of the educational setting by increasing schools' efficiency (Wong, 2003). Few empirical papers in the literature have studied the effect of quality improvement programs on schools' results (e.g., Caputo and Rastelli, 2014; Mitchell, 2015); and of these, none has taken a causal perspective to assess the impact of such programs on educational outcomes. Therefore, more research is needed in this area.

Likewise, in the current situation with high public deficits in many countries, policy makers are concerned not only to improve educational outcomes, but to do so by also taking into account the costs dimension in terms of public expenditure. This relationship between educational resources and results makes necessary to measure the impact of public programs in terms of efficiency (McEwan and Carnoy, 2000). In this environment, a myriad of papers have applied frontier methods to measure technical efficiency and TFPC in education (for an extensive overview of applied research on the measurement of technical efficiency in education see Chapter 2). The frontier approach is especially attractive in the educational context, where multiple inputs and outputs are involved in the learning process, prices are unknown or difficult to estimate, and the technology that relates the input and the output vector is completely unknown.

It is our view that an education system should always bear in mind both dimensions: effectiveness and efficiency. On one hand, we need to establish a causal link between the program and the results obtained in the treated population compared to a counterfactual group, i.e., we need to demonstrate that the program is effective. But, on the other hand, it is also crucial to relate the investment in the education system through the program and the educational results obtained by comparing total factor productivity in treated and counterfactual schools. In fact, the efficiency and effectiveness literatures have followed parallel paths. Nevertheless, only few papers have considered the two dimensions together in the analysis (e.g., Powell *et al.,* 2012; Crespo-Cebada *et al.,* 2014; Cherchye *et al.,* 2015).

More research is therefore needed in this area, especially given that educational programs can sometimes be vague or flexible in terms of the specific actions that treated schools should carry out. In these cases, analyzing the impact of the program on the average educational outcomes is not enough. Firstly, it is also necessary to benchmark best practices among treated schools in order to learn from the way they implemented the program and to translate this knowledge to inefficient schools. Secondly, total factor productivity changes should be measured to monitor that the program also improves the productivity of treated schools. This joint analysis may have important implications, providing policy makers with vital feedback for taking rational decisions.

In this chapter, we propose such joint methodology. Indeed, the main goal of this research is to assess the effectiveness and efficiency of a specific quality improvement program, by using information from a program recently applied in public schools in Catalonia. In 2010, the government approved a new Law offering public schools the opportunity to participate in a four-year strategic program (2010-2013) to improve the quality of the public education system (in terms of students' academic achievement, reduction of absenteeism and improvement of social cohesion). The program finished in 2014; however, there is no empirical evidence available assessing the impact of these education quality initiatives on schools' performance. In this chapter, we aim to respond to the following research questions: has the program achieved its goals in terms of students' academic outcomes, absenteeism and social cohesion (effectiveness)? And secondly, has the program fostered efficiency in the public education system in Catalonia?

The novelty of our approach is that it simultaneously uses an impact evaluation technique together with efficiency analysis. First, and bearing in mind the existence of causation, we use the DiD approach to test the effectiveness of the program and to study whether the participating schools achieved the objectives by comparing them with non-participating schools. Second, a Malmquist TFPC index (Caves *et al.,* 1982) is calculated in order to check the efficiency and technology changes in the schools participating in the program. Our goal is to analyze whether or not productivity of the treated schools changed in a differently way from productivity in the control schools.

Regarding the effectiveness results, on average we find that the program had a positive and statistically significant effect on treated schools' results. The frontier analysis reveals that participating schools present a positive and significant TFPC (3.7%, on average) in comparison with control schools (3%, on average).

The research reported here may make several contributions. Firstly, we apply a propensity score matching (PSM) and a DiD method using a fixed effect panel data regression model to analyze the effectiveness of such quality improvement programs. In addition, we compute productivity changes by using the Malmquist TFPC index. To date, no previous empirical studies in the economics of education literature has applied this approach. This joint approach constitutes a powerful methodology to test the results of implementing any kind of public policy or reform. Secondly, in terms of policy implications, our findings provide real evidence for policy makers on whether current policies are working or not. These results will lead to improvements in future policies and program implementation. In the same way, the information generated by impact evaluation and efficiency analysis may be useful for program sustainability and can be a valuable asset in budget negotiations and in providing reliable information to inform public opinion.

The rest of this chapter is structured as follows. Section 6.2 presents the program in detail. We explain the research design in Section 6.3. Section 6.4 describes the dataset and the selected variables included in the empirical analysis. Section 6.5 reports the results. Finally, Section 6.6 concludes by discussing the implications for public policies.

6.2 Description of the Program

6.2.1. Objectives and support from the Department of Education

Created on 10th February 2010 to be implemented in the following four academic years under the resolution EDU/381/2010, the Program to Improve the Quality of Education Institutions (*Projecte per a la Millora de la Qualitat dels Centres Educatius* –

PMQCE – EDU/381/2010, de 10 de febrer) aims to improve the quality of education in public schools by providing them with additional resources. The main goals of this program were to improve the quality of education students receive in terms of educational outcomes; to enhance social cohesion in more complex schools (those attended by students from low socio-economic backgrounds); and to reduce the level of absenteeism. The Department of Education (*Generalitat* of Catalonia - Spain) promoted this program taking into account the educational goals set by the European Union (EU) for 2020, the content of the National Agreement for Education (*Pacte Nacional per a la Educació*), the objectives of the 2007-2010 Government Plan, the Program for the support and reinforcement in public education (*Proyecto de apoyo y refuerzo en educación pública – PROA),* the Royal Decree 102/2010 on autonomy of schools (*Decret 102/2010, de 3 d'agost, d'autonomia dels centres educatius)* and the cooperation plan to support the implementation of the Educational Law *(Ley Orgánica de Educación - LOE)*, from the Ministry of Education.

The *PMQCE* was developed through a co-responsibility agreement between the school and the Department of Education. Following the same objectives as the EU for 2020, from academic years 2010-11 to 2013-14 the Department of Education promoted and prioritized the *PMQCE* co-responsibility agreements with schools to develop strategies aimed at ensuring equity and improving educational outcomes in especially disadvantaged or unique socio-economic and cultural environments, and to prevent early dropout in education. These co-responsibility agreements aimed to promote schools' autonomy, to support the schools' educational objectives, and to encourage strong leadership in school management for taking responsibility and being accountable.

Each school participating in the *PMQCE* had to define the objectives of its co-responsibility agreement according to the principles guiding the education system (following the *LOE*, schools should tailor their duties to improve educational performance in basic education, promote continuity in post-compulsory education, and follow the requirements of the knowledge society). These agreements had to include the action plan for the following four academic years (from 2010-11 to 2013-14), the uniqueness of the school and its environment, and additional resources associated, if applicable.

In this scenario, the Department of Education committed to provide schools with the educational resources needed to implement the *PMQCE*. The school committed to implement the action plan and be accountable to the school community and the educational authorities in achieving the objectives in the terms set out in the co-responsibility agreement. Specifically, the Department of Education deployed a plan to support and advise schools, through:

- Specific assistance and training from the Inspectors of Education to help schools develop an initial and final assessment and advise them on the different phases in putting the strategic plan into practice.
- Specific support from other services of the Department of Education involved in the program.
- Networking to foster the exchange of knowledge and experiences.
- New Information and Communication Technologies (NTIC) related to organization and management.
- Providing schools with additional resources to achieve the objectives, taking into account their size and complexity, the environment, their current resource allocation and the content of the strategic plan.
- Recognizing teachers who significantly participated and contributed to the program, and promoted strategic plans for improving the quality of educational services.

6.2.2 Design and formulation of the four-year strategic plan

The strategic plan for the four academic years had to take into account the following guidelines:

- The plan had to be written during the academic year 2009-2010 corresponding to the design phase.
- The plan had to stipulate the objectives to be achieved by the school in the period. The objectives were defined according to the following references: the general objectives of the education system, the environmental education plan

within the framework of the city or equivalent, and the school's education program.

- The global strategy and specific actions had to be included with the corresponding general timing. These strategies could involve: singularities of the organization and the characteristics of human resources to achieve the objectives proposed; singularities in the teachers' training needs linked to the strategic plan; the specification of the model of organizational and pedagogical management requiring the strategic plan and that the school wants to adopt; singularities in the curriculum organization; the specification of the allocation or distribution of material resources; and the specification of courses of action and processes designed to involve students and their families in developing the plan.
- An internal procedure for monitoring and evaluating the strategic plan had to be in place. The procedure was established with the advice of the Inspectors of Education and used the assessment indicators set down by the Department of Education.
- Accountability. In the strategic plan the school had to define the mechanisms and frequency for reporting to the education community on the development of the plan.

Apart from these general guidelines, the *PMQCE* did not establish any reference to specific actions to be carried out for each school. Indeed, the program was flexible regarding the content of the co-responsibility agreement; each school could draw up its own action plan bearing in mind the specific internal and/or external conditions and necessities. As a result, we are better able to justify our empirical strategy (detailed in Section 6.3). Specifically, the diversity of action plans presented obliged us to use an efficiency assessment model in order to identify best practices (for benchmarking purposes) and the best schools in terms of management of available resources.

The strategic plan had to be approved by a simple majority at the staff meeting, and by a qualified majority of two thirds of the School Board. This requirement had to be met before the agreement was presented to the Department of Education and signed. Once approved by the school, the strategic plan was presented to the Board of

Regional Educational Services or to the Department of Education, within the set deadline. On November 8th 2010 (*Resolució EDU/3639/2010 de 8 de novembre)* the Department published the list of schools approved to participate in the *PMQCE.* At this point, it is worth noting that all schools that applied for the program were selected. The Department of Education had a large enough budget to provide all schools participating in the program with the resources they needed. Once approved, the Department and the school signed a four-year agreement to implement the strategic plan.

6.2.3 Implementation and monitoring

During four academic years (from 2010-11 to 2013-14), schools coordinated and cooperated with the REAs to improve the quality of education and to achieve the goals. To do so, they received specific advice from the Inspectors of Education in each REA and additional resources from the Department of Education.

At the end of each academic year, the school was required to submit an annual report on the development and the results achieved of the strategic plan. The assessment focused on internal and external evaluation methods and self-assessment. According to the characteristics of each school's setting, the educational assessment related educational outcomes with teaching and learning resources and their management, the schools' objectives and indicators on the progress of the *PMQCE.* After the assessment, a report was issued with the results of the evaluation and providing suggestions for improvement. In addition and where appropriate, the evaluation could review the educational program, as well as any other documents concerning the structure and organization of the school; replace staff from the government and coordination bodies; review the co-responsibility agreement and the additional resources allocated to the school; and guide the teachers' participation in ongoing training and updating of their professional skills.

During the year 2013-14, the school, with the support of the Inspectors of Education, conducted a diagnostic evaluation to assess the overall results of the strategic plan.

The schools were required to present a report to the Department of Education during that academic year with information about the overall results of the strategic plan[20].

6.3 Methodology

6.3.1 Identification strategy

We use the DiD approach to estimate the impact of the *PMQCE* on students' results, absenteeism and social cohesion. This is based on a rich balanced panel data set composed of public schools in Catalonia for five academic years (2009-10 to 2013-14) that identifies the schools that signed the co-responsibility agreement with the Department of Education to participate and receive funds from the *PMQCE* (i.e., the treatment group) and those that did not (i.e., the control group). In our model, the pre-treatment period is defined as the time before the program was implemented (i.e., 2009-10) and the post-treatment period as the time in which the program was in effect (i.e., from 2010-11 to 2013-14).

In order to obtain the *PMQCE* impact on the different outcomes (i.e., students' educational outcomes, social cohesion, and absenteeism) we start by estimating the following empirical baseline model:

$$Y_{it} = \alpha + \lambda\, TREAT + \gamma_t + \gamma_i + \beta C_{it} + u_{it} \tag{6.1}$$

where Y_{it} corresponds to the outcome in school i in period t being assessed (average students' grades in Catalan, Spanish, English and Mathematics, or annual absenteeism, depending on the econometric specification); $TREAT$ is a binary program indicator that equals one if school i participates in the program and zero otherwise; γ_t is a set of time dummies, corresponding to each year of the treatment; γ_i includes a set of school dummies to take out school fixed effect[21]; C_{it} includes a set

[20] We do not have access to these evaluation results (neither annual nor final reports). Therefore, our main objective is to assess the impact of this program by using available external objective data on students' performance and schools' characteristics. This constitutes an alternative way of proving the effectiveness of the *PMQCE* without using internal data from schools, which could be biased.

[21] The balanced panel data we are using for this study allows us to observe the same school at several points in time, enabling us to control for fixed effects. We account for an indicator variable that takes

of control variables (fully explained in Section 6.4). Finally, the term u_{it} represents the error term. We estimate Eq. (6.1) by ordinary least squares, clustering by school to estimate robust errors. The coefficient λ of the previous regression estimates the average outcome gains over the four-year period observed in participating schools.

A further question is whether the program has annual effects on academic results, considering that all schools in our sample signed the agreement in 2010-11 and remained in the program until 2013-14. To explore whether the program had a different effect each year, we include an interaction of the program indicator $TREAT$ and a set of year dummies $YEAR_t$. By doing this, we capture the average effect of each year of exposure to the program. Specifically, we run the following regression:

$$Y_{it} = \alpha + \sum_{t=2010}^{2013} \delta_t \, YEAR_t * TREAT + \gamma_t + \gamma_i + \beta C_{it} + u_{it} \tag{6.2}$$

where the coefficient δ_t measures the average annual effect that the program had on treated schools.

Model from Eq. (6.2) does not control for different school-specific time trends. As Graves (2011, p.1289) states, creating a full set of school-specific time trends is not possible for computational reasons. "*The complication in estimation arises from the inclusion of both school effects and school specific time trends. School specific time trends are simply the interaction of school dummy variables with a linear trend... it creates a large and unmanageable set of variables that cannot be similarly dealt with using the areg command in Stata".* To avoid this problem, we can enrich the model from Eq. (6.2) by adding an interaction term between a set of dummy variables representing the REA in which each school is set and a time trend.

The Department of Education stated that the public education system in Catalonia is divided into ten education areas (REAs). These REAs act as local agencies in each area and each one has a team of Inspectors of Education who provide specific assistance for schools to develop the strategic plan and conduct a final assessment (explained in Section 6.2). These REAs must therefore be controlled for in the regression model. To do that, we include an interaction term between the REA dummies (REA_k) and a time

out mean differences between schools so that only changes over time in inputs and outcomes are used to identify the effects of the program. In this way, the estimation is able to control for unobserved but fixed heterogeneity across units of observation (Schlotter *et al.*, 2011).

trend variable (τ) for both treatment and control groups. By doing this, the estimation can control for unobserved but fixed heterogeneity across group of schools over time. This specific REA trend would relax the parallel trends assumption for treated and control schools by education area, and takes account of any region-specific effect in the sample. In addition, it allows each REA to exhibit independent and separate paths. Thus, the most complete empirical model would be the following:

$$Y_{it} = \alpha + \sum_{t=2010}^{2013} \delta_t \, YEAR_t * TREAT + \gamma_t + \gamma_i + \sum_{k=1}^{9} \gamma_k \, REA_k * \tau + \beta C_{it} + u_{it} \quad (6.3)$$

Before finishing this section, it is worth noting that a basic assumption behind this technique is that the remaining control variables (C), which can impact on both treated and control schools, should be invariable over time. If this is not a valid assumption, the regression analysis must control for these covariates in order to ensure a correct estimation. For this reason, we include a set of control variables in models from Eq. (6.1), (6.2) and (6.3) (these variables are described in Section 6.4).

Another key identifying assumption of this method is that trends of the treatment and the control groups are assumed to be equal in the absence of treatment. However, this assumption cannot be tested in our database. To overcome this problem, we run a PSM in the pre-treatment year (2009) to achieve more similar treated and control groups in terms of observable characteristics. PSM is one way to correct the estimation of treatment effects (in our case the impact of the program in treated versus control schools) by controlling for the existence of differences in the two groups. It is based on the idea that bias is reduced when outcomes (Y_i) are compared using treated and control units which are as similar as possible to the observable variables (C_i) that may influence selection into the treated group (Rosenbaum and Rubin, 1983). To do this, we first estimate the probability (propensity score) of signing the *PMQCE* for each school conditioning on C using a logit model.

$$p(S_i) = \frac{exp^{C_i * \gamma}}{1 - exp^{C_i * \gamma}} + \varepsilon \quad (6.4)$$

where S_i equals one if the school actually signs the *PMQCE* and zero otherwise; $p(S_i)$ is the estimated probability of participating in the *PMQCE* for school *i,* conditioned to

C_i; C_i is a set of observable characteristics; γ is a set of parameters to be estimated and ε is the error term.

Second, we use the estimated probabilities to obtain matched pairs of treated schools and their counterfactuals with a similar $p(S_i)$, but that actually are not participating in the program. We use the nearest neighbor estimator[22]—the closest school in the control group—to form the matched pairs. The result of this matching leads to a more homogeneous sample to conduct the DiD.

For proper implementation, the matching strategy has to satisfy three properties (Caliendo and Kopeing, 2008). The *unconfoundedness* property guarantees that the outcome and the treatment effect are independent, given C. The *balancing* property demands that observations with the same propensity score have the same distribution as C independently of treatment status. Thus, assignment to treatment is random for a given propensity score. Finally, the *common support restriction* requires there to be a substantial overlap between the characteristics of treated and non-treated groups, causing only very close individuals to be compared, given C.

6.3.2 Malmquist total factor productivity change index

After checking for effectiveness, our second objective is to assess the TFPC over time in treated and non-treated schools. In other words, we aim to test if the productivity of the public schools participating in the program improved as a consequence of its application. To do so, we calculate a Malmquist index (Caves *et al.* 1982). The idea behind this approach is that a program could be effective in terms of results, but not efficient if we also consider the additional resources allocated to the schools to undertake the program. At this point, it is worth noting that this frontier analysis involves the joint consideration of all students' outcomes together, not separately as in the case of DiD.

This methodology was first proposed by Caves *et al.* (1982), Berg *et al.* (1992), and Färe *et al.* (1992, 1994a, 1994b) with the aim of measuring the productivity changes

[22] There are alternative approaches for obtaining the matches. For more information on this topic, see Heckman *et al.* (1997).

within two time periods as the distance between a DMU and the frontier for each period. The approach consists of computing the geometric mean of two TFP indices (one evaluated with respect to the technology—efficiency frontier—in the period *t+1* and the other with respect to the technology in the base period *t*). The computation is based on the non-parametric DEA approach and it uses distance functions (see Coelli *et al.,* 2005). The index estimates the productivity change experienced by each DMU and it can be decomposed in two movements: the approximation of the DMU to the frontier (technical efficiency change or catching-up, EC), which measures the ability to make the best use of available technology; and the frontier shift (technological change, TC), which refers to an improvement or deterioration in the technology able to transform inputs in outputs.

Defining a vector of inputs $x = (x_1, \dots, x_i) \in \Re^{i+}$ and a vector of outputs $y = (y_1, \dots, x_k) \in \Re^{k+}$, a feasible multi-input and multi-output production technology for a period of time t *(t = 1....,T)* can be defined using the output possibility set $P^t(x^t)$. This output possibility set can be produced using the input vector x^t as $P^t(x^t) = \{y^t\colon x^t\ can\ produce\ y^t\}$, which is assumed to satisfy the set of axioms described in Färe and Primont (1995). This technology can also be defined as the output distance function proposed by Shephard (1970):

$$D^t(x^t, y^t) = inf\{\theta\colon \theta > 0, (x^t, y^t/\theta) \in \ P^t(x^t)\ \} \tag{6.5}$$

where $D^t(x^t, y^t)$ is the inverse of the factor by which the production of all output quantities could be increased in order to belong to the frontier if the inputs are kept constant. From Eq. (6.5), if $D^t(x^t, y^t) = 1$, then y^t belongs to the production set $P^t(x^t)$ and, additionally, when $D^t(x^t, y^t) < 1$, y^t the DMU is located behind the outer boundary of the output possibility set and is considered inefficient.

Then, following Caves *et al.* (1982) and Coelli *et al.* (2005), the output-based Malmquist productivity change index may be formulated as follows:

$$M_o^{t+1}(y_t, x_t, y_{t+1}, x_{t+1}) = \left[\frac{D_o^t(y_{t+1}, x_{t+1})}{D_o^t\ (y_t, x_t)} \times \frac{D_o^{t+1}(y_{t+1}, x_{t+1})}{D_o^{t+1}\ (y_t, x_t)}\right]^{1/2} \tag{6.6}$$

where the subscript *o* indicates an output orientation, *M* is the productivity of the current production point (x_{t+1}, y_{t+1}) (using period *t+1* technology) relative to the earlier production point (x_t, y_t) (using period t technology), D are output distance functions, and all other variables are as previously defined. Values higher than unity indicate positive TFPC between the two periods.

An equivalent way of writing this index is by separating the two components (EC and TC):

$$M_o^{t+1}(y_t, x_t, y_{t+1}, x_{t+1}) = EC * TC = \frac{D_o^{t+1}(y_{t+1}, x_{t+1})}{D_o^{t}(y_t, x_t)} \left[\frac{D_o^{t}(y_{t+1}, x_{t+1})}{D_o^{t+1}(y_{t+1}, x_{t+1})} \times \frac{D_o^{t}(y_t, x_t)}{D_o^{t+1}(y_t, x_t)}\right]^{1/2} \quad (6.7)$$

The first component reflects the technical EC, which captures the efficiency improvements (reductions) in period $t+1$ if $EC > 1$ ($EC < 1$), whereas $EC = 1$ indicates no changes in efficiency. The second measure represents the TC in period $t+1$ with respect to period t whose sign may be analyzed in a similar way to EC, although both measures may have different directions.

Following Grifell-Tatjé and Lovell (1994), the Malmquist index presents some advantages over traditional index numbers as it requires no assumptions, beyond monotonicity and convexity, about the production technology. In addition, it does not need to assume cost-minimizing or revenue-maximizing behavior, and prices are not needed to calculate this index.

6.4 Data and Variables

To evaluate the impact of the *PMQCE*, we use data from the Evaluation Council of the Education System in Catalonia. As in previous chapters, our data set is composed of fully public primary schools that did and did not sign the *PMQCE* in 2010. The dataset provides a large amount of information referring to the main determinants of educational achievement, represented by variables associated with students' achievement in the basic skill test, information about the families and educational environment as well as school management and educational supply. The relevant unit of observation is the school and it includes information from the academic year 2009-10 up to 2013-14.

Using this information, we build a rich balanced panel data set composed of 1,419 public primary schools over five years in Catalonia[23], covering 80% of the public education network. This panel allows a pre-treatment and a post-treatment period. As we stated before in Section 6.3.1, we define the pre-treatment period as the year before the implementation of the *PMQCE* (2009-10) and the post-treatment period corresponds to the four years in which schools received extra funds as a result of signing the *PMQCE* (2010-11 to 2013-14). By signing the agreement, schools agreed to carry out specific measures designed to improve the quality of the education provided and perform specific actions to foster the students' academic results, reduce absenteeism and improve social cohesion.

Table 6.1 summarizes the number of students and schools per year taking into account the condition of treated or control[24] and complexity of each school.

Table 6.1. Sample decomposition

Complexity / Year		2009	2010	2011	2012	2013	Number of students
Complexity A	Treated	30,691	31,005	31,512	32,078	31,778	157,064
	Control	254,160	263,140	272,683	283,335	284,147	1,357,465
Complexity B	Treated	32,527	32,640	33,331	33,556	32,900	164,954
	Control	51,072	51,940	53,502	54,593	53,998	265,105
Students per year	Treated	63,218	63,645	64,843	65,634	64,678	322,018
	Control	305,232	315,080	326,186	337,928	338,145	1,622,570
Students per year		368,450	378,725	391,028	403,562	402,823	1,944,588

		Schools per year	Total (five years)
Complexity A	Treated	81	405
	Control	1,042	5,210
Complexity B	Treated	106	530
	Control	190	950
Schools per year	Treated	187	935
	Control	1,232	6,160
Total number of schools		1,419	7,095

The estimations are computed first for the full sample; then we divide the sample into two groups of schools according to their complexity in order to check whether or not the *PMQCE* achieved the goal of improving social cohesion in more complex schools.

[23] The original number of observations was 1,570 schools per year. However, after running the PSM 151 control observations were dropped, yielding a more homogeneous sample of treated and control schools. This analysis is further explained in Section 6.5.1.

[24] For illustration purposes, we divide schools in 2009 into treated and control groups. However, the academic year 2009 is the pre-treatment period; therefore, no school had actually signed the agreement.

The Department of Education in Catalonia defines school complexity taking into consideration information from the internal and external environment of each school. The former includes information about the number of students with special educational needs, the proportion of immigrants, the number of students who arrive at school once the academic year has already started, and teacher mobility. The latter collects information about the neighborhood in terms of unemployment or socio-economic level. Schools with complexity A are the least complex.

As can be seen from Table 6.1, our balanced panel is composed of 7,095 schools in total, 1,419 schools per year, 187 of which are schools that signed the *PMQCE* (treated) and the rest, 1,232, did not (control). In terms of complexity, we find a more balanced distribution between treated and control schools for the case of complexity B (106 and 190, respectively). This finding is quite reasonable, given that they represent the schools in the greatest need of such a program. In terms of number of students, the data follow a similar trend. We have data from almost two million students divided in five years. The number of control and treated students are more similar in the case of schools with complexity B (for instance, 32,640 and 51,940, respectively for 2010) than complexity A (31,005 and 263,140, respectively, for the same year).

As stated above, the dataset provides a large amount of information on students' educational achievement in the basic skill test, on their families, on the educational environment, and on school management. Table 6.2 contains the definitions of the variables included in the current study, for the effectiveness (DiD) and productivity (Malmquist) models.

In order to develop our DiD models we use students' grades in different modules (Catalan, Spanish, English and Mathematics) and annual absenteeism as outcomes of the program (Y) (dependent variables in each DiD model). The main variable of the analysis is $TREAT$ as it collects the schools participating in the *PMQCE.* In addition, as explained above, we select a set of control variables (C) to introduce in the model. Firstly, the percentage of students with economic needs at home and the percentage of unemployed parents represent proxies of families' socio-economic level.

Table 6.2. Definition of variables

Model	Category	Variable		Description
DiD	Outcomes	Y_1	Catalan	Average grade in Catalan in the general sixth grade test.
		Y_2	Spanish	Average grade in Spanish in the general sixth grade test.
		Y_3	English	Average grade in English in the general sixth grade test.
		Y_4	Mathematics	Average grade in Mathematics in the general sixth grade test.
		Y_5	Annual Absenteeism	Percentage of student absences during the academic year (students absent more than 75% of all days).
	Question predictor	***TREAT***	Treatment	Dummy variable that indicates whether the school signed the *PMQCE* or not.
	Control variables	C_1	% Econ. needs	Percentage of students with some economic needs at home.
		C_2	% Grants	Percentage of students with grants for school meals or books.
		C_3	Unemployment Rate	Percentage of unemployed parents.
		C_4	Demand	Demand for places at school. This is the ratio of enrolment applications from parents to the places offered by the school.
Malmquist	Outputs	Y_1-Y_4	Catalan, Spanish, English and Mathematics	Average grade in the general sixth grade tests.
		Y'_5	100-Annual Absenteeism	100-Percentage of student absences during the academic year (students absent more than 75% of all days).
	Inputs	X_1	Teach/Stud	Number of teachers per 100 students.
		X_2	% No Econ. needs	Percentage of students without economic needs at home.
		X_3	Expenses/Stud	Expenses per student.

Secondly, we consider information on the percentage of students with grants for school meals or books, and finally, we include information about the demand for places at school. As deduced from Chapter 5, most families choose a school based on factors such as the location, their ideology, and their expectations of the quality of education provided in each school. For instance, it appears that if parents know that a school is going to be part of a quality improvement plan and that more money is going to be allocated to the school, then they may be more likely to apply to that school.

Following the efficiency in education literature (see Chapter 2 for a detailed review) we use as outputs (Y) the results from aptitude tests, which are homogeneous for all students. As Hoxby (2000b) states, the most important reason to choose this proxy as an output could be that both policy makers and parents use this criterion to evaluate school performance. These variables are the same as the outcome variables from the DiD estimation, the only exception being absenteeism. In this case, we use the opposite of this percentage (Y'_5 in Table 6.2)[25].

In terms of inputs, and in line with our efficiency model during the thesis, we include three inputs that are directly involved with student learning (*Teach/Stud, % No Econ. needs* and *Expenses/Stud)*. *Teach/stud* represents the number of academic staff working in the school per 100 students. The literature reveals that the number of personnel employed is a good proxy for human capital in education institutions (e.g., Haelermans *et al.,* 2012; Thieme *et al.,* 2012; Brennan *et al.,* 2014). *% No Econ. needs* proxies the socio-economic level of the families. It is expected that higher values of this variable should lead to better educational outcomes (e.g., Thieme *et al.,* 2013; Agasisti, 2014; Crespo-Cebada *et al.,* 2014). Lastly, *Expenses/Stud* refers to the operational expenses per student in each school. A higher level of spending should lead to better outcomes (Agasisti, 2014; Brennan *et al.,* 2014).

Tables 6.3 and 6.4[26] report the main descriptive statistics for the variables considered in our analysis[27]. They include the distribution of control and treatment schools within the different complexity levels and years. As can be seen from Table 6.3, treated and control schools are similar on many of the observed variables. Nevertheless, compared to the control group, treated schools presented lower students' grades in the four modules in the pre-treatment period (2009).

[25] To run the Malmquist index all outputs must be introduced in the model assuming that more is better.

[26] Note that the outcomes for the DiD estimation are equal to the outputs for the efficiency model. Therefore, to save space, Table 6.4 only includes information about the descriptive statistics for input variables.

[27] The division of treated and control schools in 2009 is for illustration purposes only.

Table 6.3. Descriptive statistics DiD variables

Full sample		*2009-Baseline year*		*2010*		*2011*		*2012*		*2013*	
		Treated	**Control**	**Treated**	**Control**	**Treated**	**Control**	**Treated**	**Control**	**Treated**	**Control**
Catalan	Mean	64.746	65.663	69.738	72.785	76.288	73.991	64.013	68.216	69.953	72.078
	St. Dev.	8.908	9.948	9.196	11.055	10.534	13.593	8.701	8.943	7.749	80450
Spanish	Mean	62.659	63.253	65.972	67.105	70.181	72.118	66.691	69.591	70.434	71.791
	St. Dev.	8.952	12.324	9.239	12.612	7.996	11.001	8.091	8.757	6.970	9.292
English	Mean	59.425	60.906	72.735	73.779	65.779	68.044	62.771	67.694	66.323	70.049
	St. Dev.	11.200	12.369	9.776	13.055	9.549	12.279	11.661	13.106	11.255	12.352
Mathematics	Mean	70.492	70.877	74.794	76.004	73.753	75.927	73.910	76.080	76.508	78.285
	St. Dev.	9.234	10.513	8.242	12.391	9.399	12.388	9.399	12.399	7.062	9.904
Annual absenteeism	Mean	2.027	1.352	3.552	2.598	2.877	1.922	2.267	1.345	1.850	0.970
	St. Dev.	3.306	2.381	3.377	2.516	3.340	2.397	3.306	2.381	3.251	2.321
% Econ. needs	Mean	13.592	13.985	14.942	7.010	15.283	7.289	16.878	7.193	15.039	7.318
	St. Dev.	13.783	9.374	14.284	9.613	15.091	9.858	16.897	10.834	14.794	9.858
% grants	Mean	29.005	28.232	29.742	21.603	28.973	19.961	29.583	21.199	30.960	20.818
	St. Dev.	15.723	14.686	15.854	15.401	15.640	14.883	15.873	15.812	18.225	16.763
Unemployment rate	Mean	19.633	19.732	17.859	16.169	18.743	16.321	18.609	16.169	6.364	7.214
	St. Dev.	9.986	7.646	11.117	7.337	11.508	7.271	11.646	7.337	10.631	7.679
Demand	Mean	0.816	0.751	0.943	0.895	0.938	0.830	0.931	0.830	1.018	0.970
	St. Dev.	0.454	0.579	0.361	0.574	0.354	0.399	0.367	0.408	0.354	0.399
	N	187	1,232	187	1,232	187	1,232	187	1,232	187	1,232

Table 6.3. Descriptive statistics DiD variables (cont)

Complexity A		*2009-Baseline year*		*2010*		*2011*		*2012*		*2013*	
		Treated	**Control**	**Treated**	**Control**	**Treated**	**Control**	**Treated**	**Control**	**Treated**	**Control**
Catalan	Mean	69.319	69.350	75.517	73.689	76.514	76.702	69.369	69.300	74.783	72.815
	St. Dev.	7.158	9.852	6.204	10.944	10.3867	13.933	5.456	8.417	4.847	9.508
Spanish	Mean	66.431	65.697	71.545	67.672	74.4314	72.909	71.440	70.353	74.075	72.389
	St. Dev.	8.190	12.510	6.177	12.739	5.7508	11.036	4.899	8.621	4.652	9.312
English	Mean	64.706	65.507	76.944	74.432	70.3015	68.846	69.276	68.811	72.144	71.212
	St. Dev.	9.887	12.125	8.743	13.316	8.5774	12.432	9.538	12.922	8.242	12.064
Mathematics	Mean	74.812	74.357	79.310	76.668	78.0231	76.881	78.180	77.033	79.930	78.950
	St. Dev.	7.395	10.472	6.795	12.517	7.3712	12.307	7.373	12.320	5.162	9.893
Annual absenteeism	Mean	1.069	0.990	2.628	2.480	1.8719	1.813	1.309	1.230	0.929	0.861
	St. Dev.	2.099	2.167	2.080	2.304	2.1705	2.183	2.099	2.167	2.036	2.106
% Econ. needs	Mean	8.041	4.729	9.247	5.185	9.1720	5.517	10.925	5.088	9.201	5.546
	St. Dev.	7.933	6.924	8.395	6.988	8.6318	7.468	10.914	6.809	8.631	7.458
% grants	Mean	21.984	18.302	22.615	19.518	22.0337	17.813	22.666	19.178	23.376	18.463
	St. Dev.	8.849	13.594	9.053	14.316	9.1706	13.452	9.277	14.664	11.048	14.797
Unemployment rate	Mean	16.535	14.437	12.032	14.986	13.8653	15.136	13.764	14.86	14.466	8.504
	St. Dev.	7.079	6.266	8.540	6.024	10.5646	5.926	10.938	6.024	12.063	7.676
Demand	Mean	0.849	0.766	1.031	0.905	1.0317	0.827	0.962	0.838	1.111	0.907
	St. Dev.	0.493	0.604	0.336	0.596	0.3039	0.396	0.345	0.417	0.303	0.396
	N	81	1,042	81	1,042	81	1,042	81	1,042	81	1,042

Table 6.3. Descriptive statistics DiD variables (cont)

Complexity B		*2009-Baseline year*		*2010*		*2011*		*2012*		*2013*	
		Treated	**Control**	**Treated**	**Control**	**Treated**	**Control**	**Treated**	**Control**	**Treated**	**Control**
Catalan	Mean	61.251	64.069	65.323	67.826	76.115	75.568	59.921	62.270	66.262	68.038
	St. Dev.	8.549	9.284	8.663	10.347	10.691	11.457	8.509	9.414	7.532	9.036
Spanish	Mean	59.777	61.296	61.713	63.995	66.934	67.780	63.062	65.412	67.651	68.513
	St. Dev.	8.455	10.527	8.936	11.428	7.967	9.746	8.185	8.324	7.177	8.482
English	Mean	55.390	57.711	69.519	70.198	62.323	63.646	57.800	61.570	61.875	63.670
	St. Dev.	10.477	11.618	9.324	10.867	8.856	10.385	10.675	12.424	11.249	11.987
Mathematics	Mean	67.191	69.191	71.343	72.364	70.490	70.699	70.648	70.854	73.893	74.642
	St. Dev.	9.165	9.650	7.577	11.017	9.501	11.524	9.501	11.529	7.218	9.167
Annual	Mean	2.760	1.735	4.258	3.247	3.646	2.520	3.000	1975	2.553	1.572
absenteeism	St. Dev.	3.841	3.253	3.968	3.389	3.846	3.280	3.841	3.253	3.796	3.198
% Econ. needs	Mean	17.834	15.179	19.295	17.017	19.953	17.006	21.426	18.741	19.501	17.035
	St. Dev.	15.705	14.678	16.235	14.625	17.199	14.610	19.151	18.725	16.869	14.610
% grants	Mean	34.370	31.916	35.188	33.042	34.277	31.741	34.869	32.280	36.756	33.738
	St. Dev.	17.641	15.146	17.712	16.142	17.427	16.765	17.766	17.264	20.423	20.636
Unemployment	Mean	22.000	21.225	22.311	22.659	22.471	22.819	22.311	22.659	17.275	13.843
rate	St. Dev.	11.199	11.196	10.825	10.036	10.825	10.036	10.825	10.036	12.973	10.786
Demand	Mean	0.791	0.707	0.875	0.844	0.867	0.843	0.907	0.790	0.947	0.923
	St. Dev.	0.423	0.417	0.366	0.435	0.374	0.416	0.383	0.351	0.374	0.416
	N	106	190	106	190	106	190	106	190	106	190

Table 6.4. Descriptive statistics efficiency variables (only inputs)

Full sample		*2009-Baseline year*		*2010*		*2011*		*2012*		*2013*	
		Treated	**Control**	**Treated**	**Control**	**Treated**	**Control**	**Treated**	**Control**	**Treated**	**Control**
Teach/Stud	Mean	8.803	10.438	8.729	10.757	8.351	9.964	6.501	8.083	7.276	9.405
	St. Dev.	1.863	4.925	1.775	6.187	1.762	5.210	1.001	3.649	1.501	5.427
% No Econ. needs	Mean	86.407	93.659	85.057	92.989	84.716	92.710	83.121	92.806	84.960	92.681
	St. Dev.	13.783	9.374	14.284	9.613	15.091	9.858	16.897	10.834	14.794	9.858
Expenses/Stud	Mean	34.906	42.919	34.324	42.062	25.745	30.522	30.393	34.218	27.565	31.123
	St. Dev.	13.950	28.630	12.383	31.706	9.125	19.602	11.420	18.772	8.938	17.106
	N	187	1,232	187	1,232	187	1,232	187	1,232	187	1,232
Complexity A											
Teach/Stud	Mean	7.896	10.511	7.850	10.909	7.372	10.048	6.126	8.171	6.681	9.497
	St. Dev.	1.039	5.461	0.914	6.570	0.977	5.477	0.653	3.752	0.778	5.458
% No Econ. needs	Mean	91.958	95.270	90.752	94.814	90.828	94.482	89.074	94.911	90.799	94.463
	St. Dev.	7.933	6.924	8.395	6.988	8.631	7.468	10.914	6.809	8.631	7.468
Expenses/Stud	Mean	28.613	43.279	28.513	42.650	20.854	30.860	26.215	37.388	23.688	31.115
	St. Dev.	7.476	29.728	6.736	33.50	4.282	20.488	8.169	19.174	5.320	17.113
	N	81	1,042	81	1,042	81	1,042	81	1,042	81	1,042
Complexity B											
Teach/Stud	Mean	9.496	10.037	9.402	9.924	9.099	9.504	6.787	7.603	7.731	8.901
	St. Dev.	2.052	3.332	1.973	3.273	1.862	3.366	1.123	2.983	1.746	5.244
% No Econ. needs	Mean	82.165	84.820	80.704	82.982	80.046	82.993	78.573	81.258	80.498	82.964
	St. Dev.	15.705	14.678	16.235	14.625	17.199	14.610	19.151	18.725	16.869	14.610
Expenses/Stud	Mean	39.715	40.943	38.765	38.834	29.482	28.668	33.586	33.264	30.528	31.164
	St. Dev.	15.755	21.598	13.824	18.736	10.048	13.659	12.506	16.406	9.975	17.112
	N	106	190	106	190	106	190	106	190	106	190

However, these differences are not significant, as is shown in the significance test after running the PSM (see Table 6.5). This fact does not change when we split the sample in terms of complexity. The same applies for annual absenteeism and control variables. In all cases, treated schools exhibit higher values in 2009. Therefore, the schools that signed the *PMQCE* were the neediest schools. Despite showing different values, as expected, differences between treated and control schools in the observed control variables tend to be highly stable over the analyzed period.

6.5 Results and Discussion

6.5.1 Effectiveness: Differences-in-differences estimates of program effect

Before applying the DiD model, we run a PSM in order to obtain unbiased comparisons between different school types. Using this technique we can match treated schools (participating in the program) with their counterfactuals to guarantee that we are comparing homogeneous groups. PSM enables us to achieve a better DiD evaluation by comparing only matched treated and control schools that have a similar probability of signing the *PMQCE*. The predictors are the same variables presented in Table 6.2 for the DiD model (Y_1-Y_5, C_1-C_4). The region of common support is (0.031, 0.884) and the balancing property is satisfied. The final number of blocks ensures that the mean propensity score is not different for treated and control schools in each block. A total of 151 control observations per year were dropped from the sample. After running the PSM, our sample of treated and control schools is more balanced and the t-test ensures that there are no statistically significant differences in the average values of the variables (see Table 6.5).

Tables 6.6-6.8 present the regression results of the three DiD models from Eq. (6.1) - (6.3) using the full sample of schools and splitting the results by complexity. At this point, it is again worth noting the main goals of the PMQCE. This program aimed to improve students' educational outcomes (basic skills in different modules) and social cohesion, and to reduce absenteeism.

Table 6.5. Differences between treated and control schools after the PSM

Variable	Mean			*t*-test	
	Treated	Control	%bias	*t*	*p*-value
Catalan	64.746	65.663	-12.6	-2.05	0.440
Spanish	62.66	63.253	-5.5	-0.55	0.585
English	59.426	60.906	-12.3	-1.17	0.242
Mathematics	70.492	70.877	-3.9	-0.38	0.707
Annual absenteeism	2.028	1.352	13.6	1.30	0.135
% Econ. needs	13.593	13.985	-3.3	-0.26	0.796
% grants	29.005	28.232	5.1	0.48	0.633
Unemployment rate	19.634	19.732	-1.1	-0.10	0.922
Demand	0.817	0.751	12.7	1.27	0.205

Therefore, we present the results of different DiD estimations, one for each module students were assessed in (i.e., Catalan, Spanish, English and Mathematics) and another one for annual absenteeism. Finally, we split the sample in two groups of schools depending on their complexity to check whether the program was effective in promoting social cohesion.

Model 1 in Tables 6.6 – 6.8 represents the base line model in which we can observe the average impact of the *PMQCE* on schools' results during the period 2010-11 to 2013-14. Table 6.6 shows that, on average, the program was effective in improving students' grades in Catalan, English and Mathematics (in 0.246, 0.183 and 0.129 standard deviations, respectively). Results for Catalan and English are the most significant and largest in magnitude. On average, we can confirm that the program did not improve academic achievement in Spanish, nor did it reduce annual absenteeism since none of these coefficients is significant.

The results that include school complexity reinforce those obtained for the full sample only in the case of less complex schools (Model 1 in Table 6.7). On average, the program was effective in improving students' grades in Catalan, Spanish, English and mathematics (in 0.258, 0.174, 0.231 and 0.164 standard deviations, respectively) but not in reducing absenteeism.

Table 6.6. Effect of the *PMCQE* on school results (full sample)

	Average grade in Catalan			*Average grade in Spanish*			*Average grade in English*			*Average grade in Mathematics*			*Annual absenteeism*		
Full sample	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Treatment	2.192***			0.531			2.052***			1.193**			0.004		
	(0.642)			(0.669)			(0.749)			(0.694)			(0.021)		
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Annual effect	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
2010 * Treat		0.881	0.801		1.146	1.127		3.930***	3.666***		1.765**	1.586**		0.029	0.018
		(0.703)	(0.699)		(0.782)	(0.784)		(0.810)	(0.804)		(0.759)	(0.759)		(0.076)	(0.077)
2011 * Treat		6.186***	5.842***		0.449	0.323		2.721***	2.413***		0.878	0.778		-0.033	-0.030
		(1.199)	(1.097)		(0.776)	(0.778)		(0.802)	(0.805)		(0.826)	(0.825)		(0.024)	(0.025)
2012 * Treat		-0.238	-0.051		-0.528	-0.428		0.149	0.299		0.971	0.858		-0.003	-0.003
		(0.698)	(0.710)		(0.776)	(0.787)		(0.942)	(0.952)		(0.834)	(0.832)		(0.003)	(0.003)
2013 * Treat		1.908***	1.731**		1.064	0.999		1.379	1.347		1.156	1.029		-0.043***	-0.039***
		(0.735)	(0.736)		(0.833)	(0.839)		(1.011)	(1.011)		(0.808)	(0.803)		(0.012)	(0.012)
REA trend	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Control variables															
% Stud. econ. needs	-0.056	-0.051	-0.0489	-0.031	-0.028	-0.019	-0.071**	-0.067**	-0.056*	-0.070**	-0.069**	-0.067*	0.001	0.001	0.001
	(0.038)	(0.038)	(0.036)	(0.035)	(0.035)	(0.035)	(0.033)	(0.034)	(0.034)	(0.035)	(0.035)	(0.035)	(0.001)	(0.001)	(0.001)
% grants	-0.014	-0.017	-0.046	-0.097**	-0.098***	-0.109***	-0.044	-0.042	-0.037	-0.051	-0.051	-0.058	-0.001	-0.001	-0.001
	(0.035)	(0.035)	(0.036)	(0.038)	(0.038)	(0.039)	(0.039)	(0.037)	(0.023)	(0.040)	(0.040)	(0.042)	(0.001)	(0.001)	(0.001)
Unemployment rate	-0.044***	-0.043**	-0.039**	-0.023	-0.021	-0.016	-0.028	-0.028	-0.029	-0.049**	-0.048**	-0.042*	-0.000	-0.000	-0.000
	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.022)	(0.023)	(0.023)	(0.021)	(0.021)	(0.022)	(0.001)	(0.001)	(0.001)
Demand	0.455	0.433	0.277	-0.076	-0.069	-0.015	0.129	0.150	0.169	0.0945	0.102	0.112	-0.014	-0.013	-0.015
	(0.424)	(0.423)	(0.423)	(0.495)	(0.495)	(0.492)	(0.453)	(0.453)	(0.451)	(0.327)	(0.328)	(0.325)	(0.016)	(0.016)	(0.016)
R^2	0.548	0.553	0.587	0.614	0.614	0.619	0.663	0.664	0.668	0.673	0.673	0.676	0.414	0.415	0.480
n		7,095			7,095			7,095			7,095			7,095	

Notes: (1) Each model represents a different DiD specification for each dependent variable (detailed in the first row). (2) All models include a set of school and year dummies. The reference year is 2009 (one year before the program starts). (3) Clustered robust errors in parentheses (the cluster variable is school id). (4) In Model 1 we do not include the annual effects of the treatment because the objective is to detect the average impact of the program. Models 2 and 3 control for the annual effect by including the interaction between the variable "treatment" and each year dummy. In addition, Model 3 also includes the REA effect by adding an interaction term between a set of dummies for each educational area and a time trend (from 0 -i.e. pre-treatment period- to 4 -i.e. last year of the program). The reference area is number 1 (Baix Llobregat) due to its size compared to the rest. (5) ***, **, and *: Below the 1%, 5% and 10% statistical significance thresholds, respectively.

Table 6.7. Effect of the *PMCQE* on school results (complexity A)

	Average grade in Catalan			*Average grade in Spanish*			*Average grade in English*			*Average grade in Mathematics*			*Annual absenteeism*		
Complexity A	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Treatment	1.847**			1.428*			2.287**			1.080*			0.007		
	(0.952)			(1.030)			(1.043)			(0.837)			(0.033)		
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Annual effect	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
2010 * Treat		2.114**	2.069**		3.189***	3.209***		3.458***	3.281***		2.134**	2.005**		0.061	0.056
		(0.979)	(0.956)		(1.108)	(1.069)		(1.154)	(1.138)		(0.967)	(0.947)		(0.116)	(0.005)
2011 * Treat		2.948**	2.634**		0.907	0.829		2.358**	2.001**		0.663	0.474		-0.023	-0.019
		(1.647)	(1.445)		(1.104)	(1.116)		(1.078)	(1.083)		(0.957)	(0.974)		(0.039)	(0.040)
2012 * Treat		0.486	0.517		0.561	0.594		1.609	1.561		0.869	0.655		-0.006	-0.005
		(1.021)	(1.038)		(1.192)	(1.199)		(1.318)	(1.328)		(0.971)	(0.986)		(0.006)	(0.006)
2013 * Treat		1.834*	1.702*		1.076	0.891		1.749	1.627		0.676	0.489		-0.004	-0.005
		(1.009)	(1.001)		(1.182)	(1.162)		(1.312)	(1.315)		(1.017)	(0.987)		(0.019)	(0.019)
REA trend	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Control variables															
% Stud. econ. needs	-0.115*	-0.111*	-0.105*	-0.077	-0.077	-0.068	-0.121**	-0.119**	-0.106*	-0.102*	-0.102*	-0.097*	0.001	0.001	0.001
	(0.059)	(0.059)	(0.059)	(0.060)	(0.061)	(0.060)	(0.055)	(0.055)	(0.055)	(0.056)	(0.056)	(0.055)	(0.002)	(0.002)	(0.002)
% grants	0.014	0.013	-0.018	-0.094*	-0.092*	-0.107**	-0.029	-0.028	-0.024	-0.038	-0.037	-0.047	-0.002	-0.002	-0.002
	(0.045)	(0.045)	(0.046)	(0.051)	(0.051)	(0.052)	(0.053)	(0.053)	(0.054)	(0.051)	(0.051)	(0.052)	(0.002)	(0.002)	(0.002)
Unemployment rate	-0.035	-0.036	-0.035	-0.004	-0.008	-0.016	-0.010	-0.015	-0.018	-0.024	-0.021	-0.016	-0.001	-0.001	-0.001
	(0.025)	(0.025)	(0.025)	(0.024)	(0.025)	(0.025)	(0.033)	(0.033)	(0.034)	(0.029)	(0.029)	(0.031)	(0.001)	(0.001)	(0.001)
Demand	0.404	0.393	0.259	-0.139	-0.132	-0.082	0.023	0.026	0.247	0.069	0.075	0.082	-0.011	-0.011	-0.012
	(0.444)	(0.445)	(0.446)	(0.531)	(0.532)	(0.528)	(0.486)	(0.486)	(0.487)	(0.346)	(0.347)	(0.345)	(0.017)	(0.017)	(0.017)
R^2	0.538	0.538	0.569	0.591	0.591	0.597	0.636	0.636	0.641	0.658	0.658	0.662	0.473	0.480	0.483
n		5,615			5,615			5,615			5,615			5,615	

Notes: (1) Each model represents a different DiD specification for each dependent variable (detailed in the first row). (2) All models include a set of school and year dummies. The reference year is 2009 (one year before the program starts). (3) Clustered robust errors in parentheses (the cluster variable is school id). (4) In Model 1 we do not include the annual effects of the treatment because the objective is to detect the average impact of the program. Models 2 and 3 control for the annual effect by including the interaction between the variable "treatment" and each year dummy. In addition, Model 3 also includes the REA effect by adding an interaction term between a set of dummies for each educational area and a time trend (from 0 -i.e. pre-treatment period- to 4 -i.e. last year of the program). The reference area is number 1 (Baix Llobregat) due to its size compared to the rest. (5) ***, **, and *: Below the 1%, 5% and 10% statistical significance thresholds, respectively.

Table 6.8. Effect of the *PMCQE* on school results (complexity B)

	Average grade in Catalan			*Average grade in Spanish*			*Average grade in English*			*Average grade in Mathematics*			*Annual absenteeism*		
Complexity B	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Treatment	1.361			-0.068			0.472			1.389			0.009		
	(0.959)			(0.990)			(1.169)			(1.170)			(0.030)		
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Annual effect	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
2010 * Treat		0.356	0.104		-0.798	-1.070		1.686	1.682		0.868	0.433		-0.017	-0.055
		(1.159)	(1.248)		(1.259)	(1.422)		(1.319)	(1.388)		(1.277)	(1.334)		(0.115)	(0.119)
2011 * Treat		3.434	2.724		0.677	0.417		1.096	1.079		1.742	1.170		-0.098***	-0.086**
		(1.816)	(1.693)		(1.242)	(1.337)		(1.277)	(1.334)		(1.427)	(1.511)		(0.036)	(0.038)
2012 * Treat		0.519	0.525		-0.885	-1.677		-1.522	-1.505		1.685	1.119		-0.001	0.002
		(1.064)	(1.128)		(1.119)	(1.211)		(1.454)	(1.601)		(1.433)	(1.507)		(0.004)	(0.004)
2013 * Treat		1.147	0.161		0.744	-0.282		0.654	0.672		1.259	0.689		-0.046***	-0.046***
		(1.145)	(1.236)		(1.252)	(1.364)		(1.619)	(1.732)		(1.309)	(1.404)		(0.017)	(0.018)
REA trend	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Control variables															
% Stud. econ. needs	0.017	0.016	-0.002	0.020	0.020	0.187	-0.022	-0.022	-0.021	-0.037	-0.037	-0.038	0.001	0.001	0.001
	(0.034)	(0.034)	(0.031)	(0.029)	(0.029)	(0.030)	(0.035)	(0.035)	(0.036)	(0.038)	(0.039)	(0.039)	(0.002)	(0.002)	(0.002)
% grants	-0.093*	-0.093*	-0.115**	-0.118**	-0.119**	-0.130**	-0.069	-0.069	-0.068	-0.084	-0.085	-0.089	0.001	0.001	0.001
	(0.051)	(0.051)	(0.054)	(0.053)	(0.053)	(0.052)	(0.046)	(0.046)	(0.046)	(0.063)	(0.063)	(0.065)	(0.001)	(0.001)	(0.001)
Unemployment rate	-0.043	-0.043	-0.055	-0.039	-0.040	-0.100**	-0.021	-0.021	-0.038	-0.091**	-0.091**	-0.159***	-0.001	-0.001	-0.001
	(0.041)	(0.041)	(0.041)	(0.042)	(0.042)	(0.046)	(0.049)	(0.049)	(0.057)	(0.046)	(0.046)	(0.052)	(0.002)	(0.002)	(0.002)
Demand	0.205	0.295	0.458	0.668	0.754	0.704	1.627	1.817	1.782	0.614	0.581	0.316	-0.033	-0.032	-0.044
	(1.213)	(1.221)	(1.219)	(1.162)	(1.173)	(1.206)	(1.231)	(1.234)	(1.222)	(1.003)	(1.013)	(0.995)	(0.045)	(0.045)	(0.047)
R^2	0.595	0.598	0.664	0.647	0.648	0.664	0.697	0.699	0.709	0.668	0.668	0.679	0.489	0.491	0.500
n		1,480			1,480			1,480			1,480			1,480	

Notes: (1) Each model represents a different DiD specification for each dependent variable (detailed in the first row). (2) All models include a set of school and year dummies. The reference year is 2009 (one year before the program starts). (3) Clustered robust errors in parentheses (the cluster variable is school id). (4) In Model 1 we do not include the annual effects of the treatment because the objective is to detect the average impact of the program. Models 2 and 3 control for the annual effect by including the interaction between the variable "treatment" and each year dummy. In addition, Model 3 also includes the REA effect by adding an interaction term between a set of dummies for each educational area and a time trend (from 0 -i.e. pre-treatment period- to 4 -i.e. last year of the program). The reference area is number 1 (Baix Llobregat) due to its size compared to the rest. (5) ***, **, and *: Below the 1%, 5% and 10% statistical significance thresholds, respectively.

Likewise, the results show a similar trend, although the impact is higher in terms of standard deviations, also revealing a significant impact in Spanish grades that was not significant for the full sample. The lack of significant impacts in the results for social cohesion from more complex schools (Model 1 in Table 6.8) supports the idea that, on average, the program did not promote social cohesion. As can be seen from the tables, we find that the program had no significant impact in any outcome in schools classified as complexity B, on average.

The above results are not sufficient to obtain valid conclusions about the effectiveness of implementing the *PMQCE.* Although some effects can be identified, on average, an annual assessment must be made since the program was active over four academic years. To do so, we run models from Eq. (6.2) and (6.3). As explained in Section 6.3.1, Model 3 is the most complete and robust estimation since it includes not only the annual effect, but also a REA trend.

When decomposing the annual effects for the full sample (Model 3 in Table 6.6), we discover that the program was not effective during the full four-year period, but only in separate years. Specially, we find a positive significant effect in Catalan for the second and fourth year (0.656 and 0.194 standard deviations, respectively), with the impact being much higher in the second than in the fourth year. Significant impacts in English grades are detected for the first two years of implementation (0.327 and 0.215 standard deviations, respectively). Again, the highest impact is found during the first year. These findings indicate that the program was more effective at the beginning than at the end of the period[28]. The significant and positive impact of the program on Mathematics during the first year of implementation reinforces this fact (0.172 standard deviations). Once again, as is shown for the average effect, the program was not able to improve students' grades in Spanish. Nevertheless, in that case the program was effective in reducing annual absenteeism in 0.012 standard deviations during the last year of implementation.

Linking these findings with the results by complexity (Model 3 in Tables 6.7 and 6.8), we can confirm that the improvement in academic achievement due to the *PMQCE* is supported and reinforced only for less complex schools in all modules, where a

[28] Results from efficiency analysis will reinforce this finding when including all outputs in the analysis.

significant positive impact also occurs in Catalan and Spanish for the first year (0.289 and 0.392 standard deviations, respectively). The program did not cause any significant improvement in the academic achievement in any module from the basic skill tests in more complex schools (columns 3, 6, 9 and 12 in Table 6.8).

However, the improvement in annual absenteeism detected for the full sample (column 15 in Table 6.6) is evident and significant only in more complex schools (column 15 in Table 6.8), not in less complex institutions (column 15 in Table 6.7). As can be seen, the program was effective in reducing absenteeism in those schools located in a more difficult environment (due to, for instance, a higher proportion of immigrants, students with special educational needs, or students with a low socio-economic level). The effects were 0.022 and 0.012 standard deviations for the second and fourth year, respectively (column 15 in Table 6.8).

The combination of these results (i. e., significant improvement in grades in less complex schools and significant reduction in absenteeism in more complex institutions) demonstrates the true effectiveness of the program in terms of social cohesion. Specifically, although more complex schools did not see significant improvements in academic results, we can confirm that they took great steps forward in terms of absenteeism. In fact, if they managed to achieve higher rates of attendance, the next step would be for them to improve students' grades, which is very positive in promoting social cohesion in schools within more complex environments.

In summary, we can conclude that, first, the program was effective in improving academic results, but only in the case of students from less complex schools. This result is more evident during the first two years of the program's implementation for all modules, although some significant effects are revealed for Catalan in the last year. Secondly, the program was also effective in reducing the level of absenteeism, but only in case of more complex schools and during the second and fourth year of implementation. This shows that more complex schools need more time to improve and that their priority is to reduce the level of absenteeism, rather than to achieve better student grades. Finally, this significant improvement in reducing absenteeism promotes social cohesion in schools within more complex environments.

6.5.2 Efficiency: Results from Malmquist total factor productivity change index

Having obtained the results on the effectiveness of the program for each outcome separately, our second objective concerns the overall efficiency in the application of the *PMQCE.* We ask whether or not the efficiency of treated schools improved more as a result of the program compared to schools that did not participate. In this case, it is important to note that we are considering the global improvement of outputs (detailed in Section 6.3.2) rather than looking at the effects of each one separately (as in the previous analysis).

Table 6.9 summarizes the results of the Malmquist TFPC index for the pre- and post-treatment periods and the decomposition in technical efficiency change (i.e., the approximation of the DMU to the frontier, which measures the ability to make the best use of available technology) and the technological change (i.e., the movement of the frontier itself, which refers to an improvement or deterioration in the technology). Values higher than unity indicate a positive change between the two periods. Table 6.9 also contains information about the mean differences between treated and control schools and *t*-test results of these differences to check for significant changes. In addition, as in the case of DiD models, we split the results by complexity.

The upper part of Table 6.9 shows the results of the TFPC for the full sample of schools. As can be seen, treated schools experienced a significantly higher TFPC than controls, on average, in the period (positive difference of 0.007 points). This is mainly because treated schools have a higher significant change in technical efficiency than controls (positive difference of 0.013 points) despite suffering a greater deterioration in technology over the period (negative difference of 0.006 points). In other words, the program was able to increase efficiency of management in the schools which signed co-responsibility agreements by globally improving all outputs (higher students' grades and lower absenteeism). This positive and significant result in technical efficiency change holds when the sample is divided by school complexity. However, technological regress is seen only in the less complex schools as more complex schools spearhead the significant improvement in TFPC.

Table 6.9. Malmquist results for the period 2009 - 2013

Index	DMUs	N	Min	Max	Mean	Std. Dev.	Difference (T-C)	t	p-value
Full sample									
Efficiency change	Control	1,232	0.763	1.232	1.025	0.053			
	Treated	187	0.949	1.131	1.038	0.031	0.013***	3.417	0.001
Technological change	Control	1,232	0.900	1.202	1.005	0.028			
	Treated	187	0.966	1.479	0.999	0.040	-0.006***	-2.748	0.006
TFPC (Malmquist)	Control	1,232	0.773	1.344	1.030	0.052			
	Treated	187	0.944	1.479	1.037	0.048	0.007*	1.828	0.068
Complexity A									
Efficiency change	Control	1,042	0.785	1.232	1.024	0.054			
	Treated	81	0.989	1.111	1.036	0.024	0.012**	2.042	0.041
Technological change	Control	1,042	0.900	1.141	1.006	0.027			
	Treated	81	0.971	1.021	0.992	0.011	-0.014***	-4.498	0.000
TFPC (Malmquist)	Control	1,042	0.806	1.344	1.030	0.053			
	Treated	81	0.984	1.098	1.028	0.024	-0.002	0.239	0.812
Complexity B									
Efficiency change	Control	190	0.763	1.227	1.028	0.051			
	Treated	106	0.949	1.131	1.040	0.035	0.012**	2.095	0.037
Technological change	Control	190	0.961	1.202	1.002	0.030			
	Treated	106	0.966	1.479	1.004	0.052	0.002	0.400	0.690
TFPC (Malmquist)	Control	190	0.773	1.275	1.030	0.048			
	Treated	106	0.944	1.479	1.044	0.059	0.014**	2.232	0.026

***, **, and *: Below the 1%, 5% and 10% statistical significance thresholds, respectively.

In order to reinforce previous results and to test whether the program was more or less efficient at different periods during its implementation, we divide the results of Malmquist TFPC index in two sub-periods, from 2009 to 2011, and from 2011 to 2013. The results are shown in Tables 6.10 and 6.11, respectively. As we can see in Table 6.10 for the full sample, again treated schools present a higher and significant TFPC than control schools (positive and significant difference of 0.016 points) due to a greater and significant technical efficiency change (0.010 points). However, in this first sub-period, unlike in the whole period (Table 6.9) the highest TFPC is exclusively led by less complex schools (complexity A) as we find no significant productivity change in more complex schools.

Table 6.10. Malmquist results for the period 2009 – 2011

Index	DMUs	N	Min	Max	Mean	Std. Dev.	Difference (T-C)	t	p-value
Full Sample									
Efficiency change	Control	1,232	0.615	1.380	1.031	0.079			
	Treated	187	0.887	1.276	1.041	0.050	0.010*	1.662	0.097
Technological change	Control	1,232	0.849	1.770	1.042	0.044			
	Treated	187	0.987	2.289	1.046	0.098	0.004	0.956	0.339
TFPC (Malmquist)	Control	1,232	0.646	1.864	1.073	0.075			
	Treated	187	0.947	2.289	1.089	0.108	0.016**	2.480	0.013
Complexity A									
Index	DMUs	N	Min	Max	Mean	Std. Dev.	Difference (T-C)	t	p-value
Efficiency change	Control	1,042	0.615	1.380	1.030	0.079			
	Treated	81	0.975	1.178	1.049	0.037	0.019**	2.069	0.039
Technological change	Control	1,042	0.849	1.366	1.041	0.039			
	Treated	81	0.987	1.072	1.030	0.019	-0.011***	-2.601	0.009
TFPC (Malmquist)	Control	1,042	0.646	1.463	1.071	0.072			
	Treated	81	1.003	1.175	1.080	0.038	0.009*	1.063	0.088
Complexity B									
Index	DMUs	N	Min	Max	Mean	Std. Dev.	Difference (T-C)	t	p-value
Efficiency change	Control	190	0.744	1.336	1.037	0.078			
	Treated	106	0.887	1.276	1.036	0.058	-0.001	-0.114	0.910
Technological change	Control	190	0.987	1.770	1.048	0.067			
	Treated	106	0.994	2.289	1.059	0.129	0.011	0.939	0.349
TFPC (Malmquist)	Control	190	0.822	1.864	1.085	0.091			
	Treated	106	0.947	2.289	1.096	0.139	0.011	0.813	0.417

***, **, and *: Below the 1%, 5% and 10% statistical significance thresholds, respectively.

These results are in line with those obtained in Section 6.5.1 when running the annual impact evaluation DiD models divided by complexity (Model 3 from Tables 6.7 and 6.8). The results reinforce the finding that the program was not only more effective in the first period and for less complex schools, but also it enhanced the technical efficiency through a significant improvement in academic achievement.

Finally, Table 6.11 contains the results for the sub-period 2011 to 2013. In the last sub-period, only more complex treated schools continue to present a TFPC greater than controls (difference of 0.018 points). This is due to a positive and significant technical efficiency change (difference of 0.024 points). Linking with the results from Section 6.5.1, this is because the more complex schools managed to significantly reduce absenteeism in the last period (column 15 in Table 6.8).

Table 6.11. Malmquist results for the period 2011 – 2013

Index	DMUs	N	Min	Max	Mean	Std. Dev.	Difference (T-C)	t	p-value
Full Sample									
Efficiency change	Control	1,232	0.629	1.748	1.021	0.085			
	Treated	187	0.908	1.271	1.037	0.053	0.016**	2.382	0.017
Technological change	Control	1,232	0.817	1.101	0.971	0.032			
	Treated	187	0.901	1.027	0.956	0.022	-0.015***	-6.128	0.000
TFPC (Malmquist)	Control	1,232	0.606	1.747	0.992	0.092			
	Treated	187	0.850	1.238	0.991	0.056	-0.001	-0.119	0.905
Complexity A									
Index	DMUs	N	Min	Max	Mean	Std. Dev.	Difference (T-C)	t	p-value
Efficiency change	Control	1,042	0.629	1.748	1.021	0.088			
	Treated	81	0.944	1.153	1.024	0.033	0.003	0.308	0.758
Technological change	Control	1,042	0.843	1.101	0.973	0.032			
	Treated	81	0.916	0.996	0.957	0.019	-0.016***	-4.421	0.000
TFPC (Malmquist)	Control	1,042	0.652	1.747	0.993	0.095			
	Treated	81	0.904	1.148	0.980	0.036	-0.013	-1.286	0.199
Complexity B									
Index	DMUs	N	Min	Max	Mean	Std. Dev.	Difference (T-C)	t	p-value
Efficiency change	Control	190	0.652	1.231	1.022	0.068			
	Treated	106	0.908	1.271	1.046	0.063	0.024***	2.957	0.003
Technological change	Control	190	0.817	1.084	0.960	0.030			
	Treated	106	0.901	1.027	0.955	0.024	-0.005	-1.346	0.179
TFPC (Malmquist)	Control	190	0.606	1.214	0.981	0.074			
	Treated	106	0.850	1.238	0.999	0.067	0.018**	2.064	0.040

***, **, and *: Below the 1%, 5% and 10% statistical significance thresholds, respectively.

However, one aspect that is worth noting is that the TFPC is lower than unity in this sub-period (in both treated and control schools) indicating a negative TFPC. This was mainly due to a technological regress for all schools in the sample (TC is always lower than unity and even more pronounced for schools addressed by the program). This fact is quite reasonable as we stated earlier in Section 6.5.1 when explaining the impact of the program in schools' results for the second period. It is worth remembering that while on the one hand, more complex schools managed to reduce absenteeism in the fourth year, on the other hand, there were not many significant impacts in less complex schools over the rest of outcomes at the end of the period (only in Catalan). In fact, less complex treated schools did not experience any significant changes in efficiency in this sub-period and again became worse in TC.

Summarizing, the *PMQCE* impacts differently on schools' performance considering all the outputs together and according to their complexity. On the one hand, the program had a positive and significant impact on the productivity of less complex schools in the first two years and, on the other hand, on more complex schools during the last sub-period. In other words, one remarkable conclusion is that while more complex schools need longer to achieve the program's goals, in less complex schools the program should be shorter because after a certain period of time it is no longer effective.

6.6 Conclusions

Education policy research pays considerable attention to the productivity and efficiency of the education sector, particularly to government expenditure in the education sector. Determining how governments can best finance and allocate scarce resources to produce quality education and the skills that individuals need to succeed in life is an integral task of the education economists. Analyses of the benefits of education have a long history in the economics of education literature (The World Bank, 2014). Many studies have established that spending on education is an investment with a return (Hanushek and Woessmann, 2007). However, the crucial factor is to improve learning outcomes, expand of schooling to enhance labor productivity, and contribute to higher and sustainable rates of national income growth (European Commission, 2010). In this framework, the next step is to establish which policies and programs can effectively improve learning outcomes.

As Schlotter *et al.* (2011) state, obtaining convincing evidence of the effects of specific education policies is not an easy task. Showing a mere correlation between a specific education program and potential outcomes is no proof that the program caused the outcome. For policy purposes, correlations are irrelevant and only causation is important. Impact evaluation methods may be useful in this sense as they are research tools that help discern the causal impact of a program or a policy initiative. In addition, they offer policy makers information on where to allocate scarce resources since they provide real evidence on whether current policies are working or not (Webbink, 2005). Under limited budgets, public policy requires evidence of what works, and what does not. Effective evaluation will inform policy makers of what is effective and enable improvements in future policies and program implementation. In addition, such evaluation can inform program design and may foster efficiency. Similarly, the information generated by impact evaluation may be useful for program sustainability, and it can be a valuable asset in budget negotiation and in the provision of reliable information to inform public opinion (Bellei, 2009). As stated in the introduction of this chapter, important efforts have been made to document, through rigorous impact assessments, the causal links between reforms and learning outcomes. However, the lack of reliable information on the effects of many education programs constitutes a research area with important information gaps that merits the highest priority in the current research (Schlotter *et al.,* 2011).

In this environment, the main goal of this study was to contribute to the literature by assessing the impact of a particular quality improvement program. Our objective was to assess the effectiveness and efficiency in the implementation of the *PMQCE* in public primary schools in Catalonia (Spain). To do so, we applied two empirical methodologies. First, and bearing in mind the existence of causation, we used an impact evaluation approach which consists of applying the DiD method together with panel data fixed effect regression analysis to test the effectiveness of the program. Second, we carried out an efficiency analysis based on the Malmquist TFPC index in order to check the technological and efficiency improvements in schools due to the application of this program.

Our findings reveal important insights about the effectiveness and efficiency of this program. Regarding effectiveness results, we find that the program was effective in improving students' grades in less complex schools during the first two years of application. In terms of social cohesion and absenteeism, we confirm that despite not improving students' results, more complex schools managed to significantly reduce the level of absenteeism by the end of the period. Regarding efficiency results, we show that the program impacts differently in productivity according to schools' complexity. On the one hand, the program has a positive impact on the productivity of less complex schools during the first two years of implementation due to a higher technical EC. On the other hand, efficiency significantly improves in more complex schools during the last period. When results from effectiveness and efficiency analysis are taken together, we can conclude by saying that while complex schools need longer to achieve the program's goals, less complex schools achieve them in a shorter period. Therefore, the program should be more concise in the time it runs and more precise in goals for less complex schools because after a certain period it is no longer effective.

In practical terms, these results not only highlight the importance of conducting causal analysis to assess the results of improvement programs, but they also highlight the importance of conditioning the delivery of resources to specific academic goals depending on the characteristics of the target. It is vital for policy makers to know how to spend educational resources in a cost-effective way. Impact evaluation methods provide convincing evidence on the effects of interventions in education. At the same time, efficiency analysis helps policy makers decide which particular public policy, reform or program brings the largest increase in schools' performance for the same amount of money. Not everything is valid and not at any cost, especially in an environment of limited resources. Finally, the results of this analysis may constitute a valuable source of information for comparison purposes. This information would be very helpful not only to understand the importance of the program, but also to compare the program with others already implemented in Spain or elsewhere.

CHAPTER 7.

CONCLUSIONS

7. CONCLUSIONS

7.1 Summary and conclusions

This thesis has taken a logical-deductive approach to pursue its main objective, namely, to conduct a multidimensional assessment of the efficiency of management in public schools in Catalonia through the application of non-parametric frontier techniques. In this process, the current economic scenario of budget constraints was also taken into account. This evaluation aims to contribute to defining better public education policies by identifying best practice examples and areas with more potential for improvements. To perform this multidimensional assessment a number of specific objectives have been addressed in each chapter. Since each chapter of the thesis includes a specific section detailing the conclusions, in this section we summarize the main conclusions in view of the results obtained. A summary of the results can be seen in Table 7.1.

In Chapter 2 we conducted an extensive review of the literature on efficiency in education in order to present the current status of this research. This review not only summarized the variables and methods used to date in many empirical studies on educational efficiency, but it also opened up possibilities for future research and, above all, it provided guidance for the development of this thesis. The study and compilation of what has been published so far in this academic stream enabled us to identify which variables and methods to apply in this thesis in order to contribute to developing this research line.

This literature review led us to several conclusions. Here, we note some of ones that have served as a guide for this thesis. First, we concluded that it is necessary to properly quantify the influence of environmental variables on student outcomes. This process will reveal the underlying mechanisms which drive the efficiency estimates, and make the evaluation more accurate. We suggested that recent models such as the conditional approach are suitable for this purpose. Following this recommendation, we applied the conditional and robust order-m model in Chapters 3, 4 and 5 of this thesis with the aim of properly including the role of environment in the analysis. In addition, we devoted one chapter (Chapter 4) exclusively to the impact of environmental factors in schools' efficiency and disentangled the direction of this relationship.

Second, we identified the need for more research into student added value, noting that a very interesting line of research would be to investigate students' evolution in educational terms over time, namely, whether the educational level at entry remained steady, improved, or worsened within a particular educational period. To this end, Chapter 6 analyzed the evolution of a set of primary schools in Catalonia in terms of productivity and efficiency changes.

Finally, in Chapter 2 we also concluded that the efficiency in education literature has made a significant effort to optimize its own models, but has neglected important issues in related fields such as the economics of education literature. In this vein, we suggested that one very fruitful line would be to focus more on the issue of causality. Bearing in mind this alternative for future research, in one chapter (Chapter 6) we combined efficiency and impact evaluation methods to find out the causal relationship between a particular education policy and students' academic achievement.

Based on the main goal of this thesis and the suggestions for future research from Chapter 2, we established the rest of the specific objectives addressed in the empirical chapters of this thesis.

Specifically, bearing in mind the current economic situation, Chapter 3 conducted a centralized efficiency assessment of public schools in order to propose a new design to make the current education network more efficient and competitive. To achieve this objective, we extended the CDEA model (including non-transferable inputs and environmental factors) to globally assess the efficiency of the public education network in Catalonia. In addition, we proposed a system to reallocate human resources in the public education network to obtain additional savings in the budget without jeopardizing the quality of education provided. The results showed that overall efficiency can be improved without losing outputs and quality, but this improvement depends on the objectives of the Department of Education. First, we demonstrated that it is possible to save 12.7% of resources without changing the current network composition. Second, it would be possible to save 17.2% of resources if the network changed by resizing the number of schools operating. An important finding emerged from this mechanism. If the proposed reallocation was carried out, we would enlarge the remaining schools. Therefore, we proved the existence of IRS in this education network. This result supported the strategy conducted by the government; however, the suggested model is selective in the reallocation of available resources and budget. Indiscriminate cuts were not made in all schools since only the worst performers were penalized.

As part of the (in)efficiency can be due to the existence of (bad) good environmental conditions, in Chapter 4 we analyzed the role of environmental factors on students' achievement by using a conditional and robust order-*m* efficiency approach. In addition, a non-parametric regression and significance tests were applied to disentangle the direction of this relationship. Our focus was to specifically analyze, using a detailed database, whether an unfavorable socio-economic background always has a negative impact on students' performance. After running the models, the empirical results revealed that the majority of environmental variables considered had a significant effect on primary schools' performance. The direction of the relationship was in line with the results obtained in the previous literature using traditional semi-parametric approaches. However, the most striking result came from the fact that when we include environmental variables in the conditional analysis, the efficiency score was worse than to the unconditional score, indicating that the scope for improvement increased and the target to achieve was more demanding. Once the non-parametric regression and the significance tests had been performed, we found that the discordant variable was the percentage of unemployed parents, which had a favorable and significant effect on efficiency. Therefore, while perhaps initially surprising, this result reinforced the hypothesis that specific negative environmental factors can positively affect schools' potential outcomes. In addition, this result also revealed that teachers and school management play an important role in motivating students to obtain the best results.

Chapter 5 supplemented previous chapters by including school location in the analysis. Our main goal was to assess the effect of competition and location on efficiency and on the demand for places in the school. This chapter provided evidence for the existence of strategic interaction among public schools. We employed a two-stage estimation procedure in which first, following the analysis in Chapter 4, a robust conditional order-*m* approach was used to estimate the efficiency of each school, and then a spatial econometric framework was applied to disentangle the correlation in the demand for school places due to the existence of strategic interaction (competition in performance and location). We also performed several additional tests to check for robustness in the results. Overall, the results confirmed our hypotheses as we found that first, in an enrollment system with increasing choices, parents perceive the quality of school management (which resembles efficiency score) when applying for a school. Therefore, parents take into account not only location when selecting a school, but also their perception of performance. In addition, the findings supported the hypothesis that competition matters, and reveal important differences in demand for schools across Catalonia. We found that increased demand for neighboring schools led to higher demand for the school under assessment, revealing the presence of positive spatial autocorrelation. That said, it does not immediately follow that new sources of competition will have similar positive effects, as the performance of neighboring schools was found to have diminishing effects on the demand for a particular school, proving the existence of competition in the public education sector.

Finally, Chapter 6 closed the empirical analysis of this thesis by developing a longitudinal analysis of the effectiveness and efficiency of public schools in implementing a specific quality improvement program. As stated earlier, the approach proposed in this chapter is innovative in that it takes into account two types of analysis: effectiveness and efficiency. The DiD approach with fixed effects panel data regressions was applied to disentangle the impact of this four-year program on students' academic performance. In addition, the Malmquist TFPC index was developed to extend our knowledge on the evolution of productivity and efficiency of schools that implemented the program.

Our findings revealed important information about the effectiveness and efficiency of this program. Regarding effectiveness results, we found that the program was effective in improving students' grades in all modules, but only in less complex schools and just for the first two years of application. In terms of social cohesion and absenteeism, we confirmed that despite not improving students' results, more complex schools managed to significantly reduce the level of absenteeism by the end of the period. Results from the efficiency analysis reinforced these conclusions since we proved that the program impacted differently on productivity depending on schools' complexity. On the one hand, the program had a positive impact on the productivity of less complex schools during the first two years of implementation due to a higher technical EC. On the other hand, efficiency in more complex schools significantly improved during the later period. Taking these results together, we concluded that while complex schools needed more time to accomplish the goals of the program, less complex schools were able to achieve them in a shorter period.

Finally, as an implication for management practices, we mentioned that the program should be more concise in the time period and more precise in its goals depending on the characteristics of the target, since after a certain period it is no longer effective in less complex schools. In practical terms, these results highlighted not only the importance of conducting causal analysis to assess the results from implementing improvement programs, but also the importance of conditioning the delivery of resources to specific academic goals depending on the characteristics of the target, and even more so in an scenario of budget constraints.

Table 7.1. Summary of the main results of the thesis

Chapter	Objective	Methodology	Main results
2	To review the literature on efficiency in education.	Extensive literature review from 1977 to 2015.	Summary of the level of analysis, inputs, outputs and environmental variables applied, methodology used and suggestions for future research.
3	To conduct a centralized efficiency assessment to redesign the public education network.	Extended CDEA, incorporating the effect of non-transferable inputs and environmental factors + conditional order-*m*. Sample of 161 public primary schools in *Vallès Occidental* (Catalonia) for the academic year 2009-10.	12.7% of resources can be saved without changing the current network composition. However, this saving could rise to17.2% if the network changed by resizing the number of schools operating. In this reallocation, the level of outputs and quality would be maintained; indiscriminate cuts were not made in all schools since only the worst performers were penalized.
4	To assess the impact of environmental factors on efficiency.	Unconditional and conditional order-*m* models + non-parametric regression + significance tests. Sample of 1,694 public primary schools from Catalonia for the academic year 2009-10.	The majority of the environmental variables considered had a significant effect on primary schools' performance. The direction of the relationship was in line with the results obtained in the previous literature. However, the percentage of unemployed parents showed a favorable and significant effect on efficiency. This result proves that specific negative environmental factors can positively affect schools' potential outcomes.
5	To assess the effect of competition and location on efficiency and on the demand for places in the school.	Conditional order-*m* model + spatial regression analysis. Sample of 1,127 public primary schools from urban municipalities in Catalonia for the academic year 2009-10.	Parents take into account location and their perception of performance when selecting a school. In addition, competition matters in public education and important differences were revealed in demand for schools across Catalonia. Increased demand for neighboring schools led to higher demand for the school under assessment; however, higher performance of neighboring schools had diminishing effects on the demand for a school.
6	To assess the effectiveness and efficiency of public schools in the application of a specific quality improvement program in education.	DiD regression model with panel data + Malmquist TFPC index. Panel of 1,419 public primary schools from Catalonia for the academic years 2009-10 to 2013-14.	The program was effective in improving students' grades in less complex schools and during the first two years of application. More complex schools managed to significantly reduce the level of absenteeism by the end of the period. In addition, the program had a positive impact on the productivity of less complex schools during the first two years due to a higher technical EC. Lastly, efficiency in more complex schools significantly improved during the last period.

7.2 Contributions and directions for future research

As highlighted in Chapter 1, this thesis might make both academic and managerial contributions. From the academic point of view, this research may contribute to the generation of knowledge in an area that still has room for deeper understanding, as some aspects remain unaddressed.

This thesis has shown that non-parametric efficiency methods such as CDEA, the Malmquist index and order-*m* models constitute a powerful methodology that can be used to assess and monitor the performance of public schools. One important feature of these techniques is their ability to overcome the subjectivity associated with the specification of the functional form of the production process present in most assessments involving intangible production processes, such as the education sector. By relying on an optimization process, these methods have the advantage of estimating performance by comparing with observed best practices, so they are ideal for conducting benchmarking initiatives leading to continuous improvement.

The thesis contributes to the field of performance management in its use of several non-parametric frontier methods. Innovative and sophisticated models were developed to address empirical issues in the education field, as described in the following summaries of the main methodological contributions of the thesis:

- The development of an extended CDEA model that can incorporate non-transferable inputs and environmental factors to assess the overall performance of a group of DMUs.

- The design of an iterative process to reallocate human resources based on efficiency ranking and geographical distance between DMUs.

- The application of novel and robust models of efficiency assessment, such as the conditional order-*m* model, to incorporate the role of environmental factors in the analysis.

- The definition of a conceptual model to assess demand for places in public schools, including the role of location and competition.

- The assessment of demand for places in public schools by applying a new approach in the education literature rarely used so far. This model combines efficiency analysis and spatial econometrics techniques.

- The simultaneous study of effectiveness and efficiency in the education sector, which has rarely been considered in previous studies.

- The implementation of a DiD model to control for causality in the application of an improvement program in public education.

- The analysis of productivity and efficiency changes over time through the application of the Malmquist TFPC index involving the inclusion of desirable and undesirable outputs.

In addition, the systematic literature review applied in Chapter 2 may contribute to the development of the research stream about efficiency in education by summarizing the major contributions in the literature.

Similarly, the results of this thesis are also helpful in drawing up government policies designed to promote and foster quality in public education. More specifically, besides providing decision makers with information to help them understand how schools actually perform with the available resources, it is also possible to identify the steps to be taken to improve performance, and to manage the public education budget more efficiently. In addition, benchmarking studies provide opportunities for any stakeholder interested in education to learn with the best practices and to establish strategies to improve students' attainment and the quality of education provided. As we have shown, improvements in these fields can lead to competitive advantages for schools, as they compete against each other to attract more resources and students, and parents take these factors into account when deciding on a particular school.

To conclude, this thesis provides novel answers to important questions, but naturally, it also raises other questions and opens the door to new lines of future research.

Apart from the specific limitations suggested in each chapter of this thesis, it is worth pointing out some general shortcomings in directions for future research in the field of education. These suggestions are summarized below in no particular order of importance.

Firstly, it would be interesting to compare the results obtained in the empirical part of this thesis (Chapters 3, 4, 5 and 6) based on non-parametric models, with results obtained from alternative frontier methods, such as SFA. The comparison with other frontier methods could provide additional validation of the results.

In addition, it would be very fruitful to undertake a dynamic efficiency analysis, by applying a more robust efficiency method than the one run in Chapter 6 with the Malmquist TFPC index. In fact, the application of dynamic DEA (Tone and Tsutsui, 2010; 2014) is attracting more attention in the efficiency literature, but not yet in the particular stream of education.

Furthermore and closely related to the previous point, we believe that further research is needed on the issues related to incorporating environmental factors in the assessment of productivity changes over time.

Similarly, the empirical analysis developed could be enriched with the consideration of private schools. Once the data to be available, we could complete the analysis comparing public and private institutions.

Finally, our strategy to combine the causal inference with efficiency in this thesis is rooted in the impact evaluation literature (Chapter 6). In this direction, it would be a promising future line to investigate how the results of the DiD model from Chapter 6 could change when considering instrumental variables in the analysis instead of working with real educational outcomes.

APPENDIX

APPENDIX TO CHAPTER 2

Table A1: Data sets used in the literature about efficiency in education

Data from another paper	Bessent and Bessent (1980), Ray and Mukherjee (1998), Wang (2003), Millimet and Collier (2008).
Data from educational programs (Follow Through, Integrated Secondary Data System, SiBO-project)	Charnes *et al.* (1981), Robst (2001), Cherchye *et al.* (2010).
GCSE Data (General Certificate of Education Advanced Level)	Thanassoulis and Dunstan (1994), Thanassoulis (1999), Portela and Thanassoulis (2001), Thanassoulis and Portela (2002), De Witte *et al.* (2010).
National Data Bases from the Department of Education/Employment or similar	Bessent *et al.* (1982), Butler and Monk (1985), Sengupta and Sfeir (1986) (1988), Jesson *et al.* (1987), Sengupta (1987), Smith and Mayston (1987), Mayston and Jesson (1988), Färe *et al.* (1989), Taylor and Johnes (1989), Beasley (1990), Callan and Santerre (1990), Diamond and Medewitz (1990), Barrow (1991), Ray (1991), Ganley and Cubbin (1992), Kao and Yang (1992), Deller and Rudnicki (1993), Johnes and Johnes (1993) (1995) (2009), McCarty and Yaisawarng (1993), Bonesrønning and Rattsø (1994), Sinuany-Stern *et al.* (1994), Chalos and Cherian (1995), Ruggiero *et al.* (1995), Cubbin and Zamani (1996), Engert (1996), Jimenez and Paqueo (1996), Johnes (1996) (2006a) (2006b) (2006c) (2008) (2014), Mar-Molinero (1996), Ruggiero (1996a) (1996b) (2000) (2007), Thanassoulis (1996), Athanassopoulos and Shale (1997), Bates (1997), Duncombe *et al.* (1997), Grosskopf *et al.* (1997) (1999) (2001) (2009) (2014), Heshmati and Kumbhakar (1997), McMillan and Datta (1998), Ruggiero and Bretschneider (1998), Ruggiero and Vitaliano (1999), Mancebón and Mar-Molinero (2000), McEwan and Carnoy (2000), Thursby (2000), Ying and Sung (2000), Avkiran (2001), Bradley *et al.* (2001) (2010), Chakraborty *et al.* (2001), Daneshvary and Clauretie (2001), Gershberg and Schuermann (2001), Grosskopf and Moutray (2001), Abbott and Doucouliagos (2002) (2003) (2009), Fukuyama and Weber (2002), Izadi *et al.* (2002), Mizala *et al.* (2002), Moreno and Tadepali (2002), Muñiz (2002), Emrouznejad and Thanassoulis (2005), Kiong *et al.* (2005), Oliveira and Santos (2005), Ouellette and Vierstraete (2005), Casu and Thanassoulis (2006), Koksal and Nalcaci (2006), Agasisti and Salerno (2007), Fandel (2007), Rassouli-Currier (2007), Waldo (2007a) (2007b), Conroy and Arguea (2008), Johnes *et al.* (2008), Kao and Hung (2008), Kuo and Ho (2008), Mancebón and Muñiz (2008), Millimet and Collier (2008), Worthington and Lee (2008), Agasisti and Dal Bianco (2009), Agasisti and Johnes (2009) (2010), Colin-Glass *et al.* (2009), Kantabutra (2009), Sarrico and Rosa (2009), Alexander *et al.* (2010), Carpenter and Noller (2010), Essid *et al.* (2010) (2013) (2014), Houck *et al.* (2010), Kempkes and Pohl (2010), Kantabutra and Tang (2010), Khalili *et al.* (2010), Katharaki and Katharakis (2010), Ouellette and Vierstraete (2010), Portela and Camanho (2010), Rayeni and Saljooghi (2010), Sarrico *et al.* (2010), Agasisti *et al.* (2011) (2012), Johnes and Schwarzenberger (2011), Kounetas *et al.* (2011), Lee (2011), Mongan *et al.* (2011), Thanassoulis *et al.* (2011), Eff *et al.* (2012), Gronberg *et al.* (2012), Haelermans and Blank (2012), Haelermans and De Witte (2012), Haelermans *et al.* (2012), Johnes *et al.* (2012), Kirjavainen (2012), Misra *et al.* (2012), Portela *et al.* (2012) (2013), Sexton *et al.* (2012), Tochkov *et al.* (2012), Burney *et al.* (2013), Haelermans and Ruggiero (2013), Johnes (2013), Lu and Chen (2013), Thieme *et al.* (2013), Zoghbi *et al.* (2013), Agasisti and Bonomi (2014), Blackburn *et al.* (2014), Brennan *et al.* (2014), Johnson and Ruggiero (2014), Mainardes *et al.* (2014), Mayston (2014), Nazarko and Saparauskas (2014), Podinovski *et al.* (2014).

Table A1: Data sets used in the literature about efficiency in education (cont)

Other OECD Data (than PISA and TIMSS)
Kocher *et al.* (2006), Agasisti (2011b), Aristovnik and Obadic (2014).
Other Databases (Econlit, Eurostat, UNESCO, World Bank's World Depelopment database, PIRLS)
Sarrico and Dyson (2000), Cokgezen (2009), Aristovnik and Obadic (2014), Cordero *et al.* (2015c).
Own data (questionnaires, public data from web sites, registers, quality assessment reports, university rankings, etc.)
Breu and Raab (1994), Beasley (1995), Chalos (1997), Cooper and Cohn (1997), Madden *et al.* (1997), Cengiz and Yuki (1998), Kirjavainen and Loikkanen (1998), Mancebón and Bandrés (1999), Ruggiero (1999), Colbert *et al.* (2000), Korhonen *et al.* (2001), Abbott and Doucouliagos (2003), Dolton *et al.* (2003), Banker *et al.* (2004), Flegg *et al.* (2004), Cherchye and Vanden Abeele (2005), Joumady and Ris (2005), Stevens (2005), Bonaccorsi *et al.* (2006), Bougnol and Dulá (2006), Giménez and Martínez (2006), McMillan and Chan (2006), Primont and Domazlicky (2006), Anderson *et al.* (2007), Tauer *et al.* (2007), Cordero-Ferrera *et al.* (2008) (2010), Johnes and Yu (2008), Ray and Jeon (2008), Abramo and D'Angelo (2009), Denaux (2009), Hu *et al.* (2009), Tyagi *et al.* (2009), Agasisti and Pérez-Esparrells (2010), Davutyan *et al.* (2010), De Witte and Rogge (2010) (2011), Dehnokhalaji *et al.* (2010), Naper (2010), Wolszczak-Derlacz and Parteka (2011), Haelermans and Blank (2012), Haelermans and De Witte (2012), Haelermans *et al.* (2012), Kirjavainen (2012), Kong and Fu (2012), Montoneri *et al.* (2012), Bayraktar *et al.* (2013), De Witte and Hudrlikova (2013), De Witte *et al.* (2013), Duh *et al.* (2014).
PISA Data (Programme for International Student Assessment)
Afonso and Aubyn (2006), Agasisti and Dal Bianco (2006), Agasisti (2011a), Cordero-Ferrera *et al.* (2011), Perelman and Santín (2011a) (2011b), Mancebón *et al.* (2012), Thieme *et al.* (2012), Agasisti (2013) (2014), Aristovnik (2013), De Witte and Kortelainen (2013), Deutsch *et al.* (2013), Crespo-Cebada *et al.* (2014).
TIMSS Data (Trends in International Mathematics and Science Study)
Hanushek and Luque (2003), Giménez *et al.* (2007).

Examples of national databases are the IGAP (Illinois Goal Assessment Program), ISBE (Illinois State Board of Education), HSMS (Household School Matching Survey Project, Philippines), CAR (Comprehensive Assessment Report) and PEP (Pupil Evaluation Program) from New York State, TEAMS (Texas Education Assessment of Minimum Skills), SIMCE (*Sistema Nacional de Evaluación de Calidad de la Educación*, Chile), NRC (National Research Council Survey, USA), ACT (American College Tests), The Annual Performance Assessment Scheme in Turkey, AVES (Evaluation of Schools with Secondary Education, Portugal), QuESTIO, survey developed by the Lombardy Regional Government, The National Operative of Educational Quality Evaluation of the Argentine Republic, NAPLAN Database developed by the Commonwealth Government in Australia, CAUBO (Canadian Association of University Business Officers), HESA (Higher Education Statistical Agency) in UK and SAT standardized test scores.

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