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DOCUMENTS DE TRAVAIL 304

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Avril 2025

ined
INSTITUT NATIONAL D'ÉTUDES DÉMOGRAPHIQUES

https://doi.org/10.48756/ined-dt-304.0425

Private vs. Public Schooling: The Role of School Composition

Elke Claes*, Léonard Moulin†

Abstract

Publicly funded private schooling is a common feature of many education systems, yet its implications for educational equity and effectiveness remain contested. While private schools often exhibit higher student achievement, the sources of this advantage are not well understood. In particular, differences in student composition – especially in terms of socioeconomic status (SES) – are likely to play a key role. This paper examines how school-level SES composition contributes to achievement differences between public and private schools. Using propensity score matching (PSM) on data from 22,441 French ninth-grade students, we find that private school students outperform their public school peers in math and French, with especially large effects for low-SES students, an underrepresented group in private schools. While school composition explains these effects only to a limited extent, it accounts for most of the performance gap among high-SES students. These findings highlight which students benefit most from private schooling and point to the need for further research into the mechanisms underlying performance differences across school sectors.

Keywords: Private school; School composition; Educational achievement; Propensity score matching; Lower secondary education.

JEL code: I21; I24.

*Research Centre for Education and the Labour Market (ROA) - Maastricht University. Email: e.claes@maastrichtuniversity.nl

†Corresponding author. Institut national d'études démographiques (INED), F-93300 Aubervilliers, France. Email: leonard.moulin@ined.fr

1 Introduction

Schools play an important role in shaping academic outcomes, but they are not all alike. Since Coleman *et al.* (1982) has demonstrated private schools' academic superiority and their role in desegregation, research has increasingly focused on differences between private and public schools. However, students in private schools differ from the ones in public schools due to selection; as they typically come from privileged families, with better-educated parents and stronger academic skills (Thapa, 2015). This complicates an assessment of the effect of private schooling on student performance. Nevertheless, several studies have addressed this effect using varying methodologies such as an IV approach, exploiting lotery systems, fixed-effects estimation, or propensity score matching.[1] Regardless of how selection bias is addressed, it seems evident that attending charter schools can have a positive impact on students' test scores in the US (e.g., Abdulkadiroğlu *et al.*, 2011; Angrist *et al.*, 2010, 2013, 2016). Private schools, moreover, tend to outperform public schools (e.g., Anand *et al.*, 2009; Azam *et al.*, 2016; Cox and Jimenez, 1990; Lefebvre *et al.*, 2011; Thapa, 2015; Wamalwa and Burns, 2018).[2]

While private schooling has generally been shown to have a positive impact on student achievement internationally, the unique structure of private schools in France warrants separate consideration. Private schools in France differ significantly from those in other countries. Most private lower secondary schools are under contract with the state, receiving substantial public funding for teachers' salaries and operating costs. These schools, often referred to as government-dependent schools, follow the same curriculum as public schools and are highly dependent on state support, resembling charter schools in the USA or free schools in the UK. However, unlike charter and free schools, private schools in France require certified teachers, can select students, and must adhere to the national curriculum. Several studies have examined the effect of private schooling on student performance in France, generally reporting positive effects (e.g., Bertola, 2017; Caille, 2004; Cayouette-Remblière *et al.*, 2019; Langouët and Léger, 1990). However, others find more

[1]First, several studies use an IV approach, mainly in assessing the impact of Catholic schooling. They instrument the choice of attending Catholic school by instruments such as Catholic region (Evans and Schwab, 1995), school attendance in a predominantly Catholic area (Evans and Schwab, 1995), and Catholic schools per square mile (Neal, 1997). Second, the impact of a type of schooling could be assessed by exploiting lottery systems, mostly used to examine the effect of charter schools in the US (e.g., Chabrier *et al.*, 2016). As highlighted by Spees and Lauen (2019), the applicability of these studies is however limited, as their results are relevant only to charter schools where the number of applicants exceeds the available spots. Third, fixed-effect estimation with longitudinal data can offer valuable insights, but its application is limited to students who change between different types of schools (e.g., Epple *et al.*, 2016). Last, propensity score matching, which relies on the assumption that all relevant confounders are observed (selection on observables), is also used to assess the effect of private schooling on student performance (Epple *et al.*, 2016).

[2]In contrast, some studies have found that attending charter or private schools offers no clear advantage, and in some cases, may even have a negative impact on student achievement (e.g., Abdulkadiroğlu *et al.*, 2018; Bifulco and Ladd, 2006; Bettinger, 2005; Chudgar and Quin, 2012; Newhouse and Beegle, 2006; Ni and Rorrer, 2012).

mixed or even negative results, particularly regarding grade retention and long-term academic outcomes (e.g., Tavan, 2004; Valdenaire, 2011). While most of these studies rely on relatively weak identification strategies, more recent research using causal inference methods provides more robust insights. Fougère *et al.* (2017), focusing on primary education, use the distance between the nearest private and public schools as an instrument – a strategy that raises concerns due to potential socioeconomic sorting, as school proximity may influence the composition of families in the area. In contrast, Moulin (2023), applying propensity score matching, finds a significant positive effect of private schooling on ninth-grade test scores.

While nearly all studies examining the effect of private schooling on student performance account for students' individual socioeconomic backgrounds, none – to our knowledge – explicitly consider the socioeconomic composition of schools. Yet, school composition plays a crucial role in shaping learning environments, as it can influence peer effects, teaching strategies, and overall academic expectations. This paper aims to fill this gap by investigating whether school SES composition[3] drives the observed differences in student performance between private and public schools. More specifically, we consider French and math scores of French ninth-grade students. Furthermore, we examine heterogeneity at student-level SES. We assess whether the effects of private schooling differ between low- and high-SES students, and whether school SES plays a different role for both groups.

We use French data from the Direction de l'Évaluation, de la Prospective et de la Performance (DEPP) of 22,441 ninth-grade students. The data include students' ninth-grade performance in math and French, complemented with information about their parental, family, and scholastic background. They contain information about the school SES, measured as the proportion of students of high-SES (see Table A.1 in Appendix) within the school and the student SES, measured by the socio-occupational category of householder. To estimate the effect of school SES composition on student achievement while addressing selection bias, we apply propensity score matching (PSM), a method that allows us to compare students with similar observable characteristics across school types. We find that school composition explains only a small portion, approximately 15-23%, of the private school advantage. Notably, private schooling proves especially beneficial for students from low socioeconomic status (SES) backgrounds, though their limited representation in private schools restricts access to these advantages. For high-SES students, initial performance gains associated with private schooling diminish when differences in school composition are taken into account, indicating that these advantages largely stem from the concentration of advantaged peers.

Given the established performance differences between public and private schools, the question consequently arises of why these differences between schools exist. We argue that these differences could stem from the composition of their student bodies, based on the

[3]Referred to as school SES in the remainder of the paper.

work of Dronkers and Robert (2008). Using PISA data from 22 countries, they examine whether the academic advantage associated with private schooling can be partly explained by school composition. They distinguish private government-dependent from private independent schools in their analyses, and conclude that private schools outperform public schools. Dronkers and Robert (2008) focus in their work, among others, on how school composition might explain achievement differences between public and private schools. Using a cross-national multilevel analysis, they demonstrate that school composition explains a large part of the achievement difference between private government-dependent and public schools. School climate differences are mentioned as an important explanation for this achievement difference. For the difference between private-independent schools and public schools, they find that the initial positive effect of private schools on student achievement reverses and becomes negative once school composition is considered.

We contribute to the literature on private schooling in two ways. The first contribution of this paper to this strand of literature is that we examine whether school composition with regard to SES can explain performance differences between private and public schools. While private schools often attract students from higher SES backgrounds, the extent to which their benefits persist when accounting for school SES remains underexplored. To the best of our knowledge, only the work of Dronkers and Robert (2008) addresses this matter. We, however, enrich their work by applying propensity score matching to deal with selection bias, which was not accounted for their analyses. Furthermore, we do not have a cross-national focus, but we focus on the French case. In France, private schooling is a widely debated policy issue, yet little is known about the factors that shape its impact on student performance. One such factor could be the school SES. Several studies examine the relationship between school SES and students' outcomes (e.g., Early *et al.*, 2020; Kim, 2019; Kim *et al.*, 2019; Sirin, 2005; Tan *et al.*, 2023). Tan *et al.* (2023), for instance, conclude in their meta-analysis on a strong association between school SES and student outcomes. Perry and Mcconney (2010), who examine this association using PISA data from more than 12,000 students from Australia, add that there is no heterogeneity in this regard to individual SES. Sirin (2005) concludes in his meta-analysis that school SES significantly impacts academic achievement, beyond the individual SES of students.

There are several reasons to suspect that school SES is a mechanism in the effect of private schooling on student performance. First, high-SES schools might have access to greater financial and material resources, enabling them to invest in better facilities, advanced technology, and enriched extracurricular opportunities. These resources might directly enhance the quality of education and indirectly support students' development. Second, the school climate might differ in schools with a low or high social composition. Schools with a higher SES composition might foster a culture of academic engagement, peer support, and aspirational learning norms. Students in such environments benefit from exposure to peers who model positive academic behaviors and attitudes, as Hanushek *et al.* (2003) show that peers significantly affect student performance. Third, teachers matter for academic achievement (e.g., Clotfelter *et al.*, 2007) and the way in which teachers are appointed differs among private and public schools. Furthermore, teachers and teaching might differ among schools with varying school SES compositions. Schools with higher SES might be more attractive for teachers, as these schools typically consist of an 'easier' student population. Teachers in higher SES schools might maintain higher expectations for their students, which is important for academic performance (Rosenthal and Jacobson, 1968). Timmermans *et al.* (2016) show that teacher experiences differ depending on student characteristics and behaviors (e.g., the student's self-confidence, social behavior in classroom, work habits etc.). And last, higher SES schools might benefit from greater parental involvement as parents choose their students to go to private school, making them interested in schooling.

The second contribution to the understanding of private and public schooling relates to heterogeneity. We investigate whether the effect of private schooling on student performance varies between low- and high-SES students, not previously addressed in the existing literature. Previous literature on heterogeneity in the effects of private schooling shows that private schools tend to be more beneficial for initially low-performing students (e.g., Abdulkadiroğlu *et al.*, 2011; Angrist *et al.*, 2010, 2013, 2016; Chabrier *et al.*, 2016; Moulin, 2023) compared to their peers. It is, however, interesting to know whether the effect of private and public schooling differs between low-SES and high-SES students, despite this already established heterogeneity. While there is often a relationship between socioeconomic status and academic performance, they are distinct factors that may interact differently with school type. So, examining SES heterogeneity could help policymakers and educators better target interventions and resources to support students from different socioeconomic backgrounds, regardless of their current academic performance.

This paper proceeds as follows: Section 2 presents the institutional background, the data, and descriptive statistics. Section 3 details the estimation strategy. Section 4 reports the results. Section 5 offers a discussion and concludes.

2 Institutional background, data, and descriptive statistics

2.1 Private schools in France

The French education system comprises four levels: *maternelle* (kindergarten, 3 years), *primaire* (primary school, 5 years covering 1st to 5th grades), *collège* (lower secondary school, 4 years covering 6th to 9th grades), and *lycée* (upper secondary school, 3 years covering 10th to 12th grades). Private education plays a significant role in France, especially at the lower secondary level, where 21.5% of students in collège were enrolled in private schools in 2019 (Moulin, 2023). A distinction is made between students in private lower secondary schools under contract with the state (*collèges privés sous contrat*) and independent private lower secondary schools (*collèges privés hors contrat*). The former represents the largest portion of the students (98%). Private schools under contract of the state operate under government regulation and receive state funding. Therefore, these schools must adhere to the national curriculum, pursue the same pedagogical objectives, and maintain equivalent academic standards as public schools. In Catholic lower secondary schools, tuition fees average €849 per year (Cour des comptes, 2023).[4] In contrast, the small percentage of students in independent private schools attend institutions with greater autonomy, but these schools receive no government funding and charge higher fees.

Private schools under contract of the state, in which we focus in this paper, mainly differ to public school in terms of student and teacher assignment. Public schools enroll students based on strict residential zoning rules, whereas contract private schools have the autonomy to select their students based on academic achievement and motivation. Admission decisions are made at the discretion of the school head, and there are no standardized entrance exams. In addition, teachers in private schools under contract of the state schools are recruited through national competitive examinations and are funded by the state. Nevertheless, unlike their public school counterparts, they are neither civil servants nor assigned to the school through a strict administrative procedure. These two points of flexibility allow private schools to cultivate distinct educational environments, which may contribute to greater cohesion among teaching staff and students.

2.2 Data

We use French data from the Direction de l'Évaluation, de la Prospective et de la Performance (DEPP), a department within the French Ministry of National Education and Higher Education. The data consist of information on a balanced random sample of 34,986 students, or 1/22 of sixth-grade students from 2007, tracked through 2013. They include detailed socioeconomic and educational records, complemented by family surveys conducted in 2008 and 2011 to capture additional socioeconomic details. The sample was carefully designed to represent the broader population using comprehensive data on students and schools.

The total data consist of information about 34,986 students. We restrict the sample to students who were expected to take the brevet examination in 2011 or 2012 (n = 30,161). We exclude students who do not have standardized test scores in either math or French

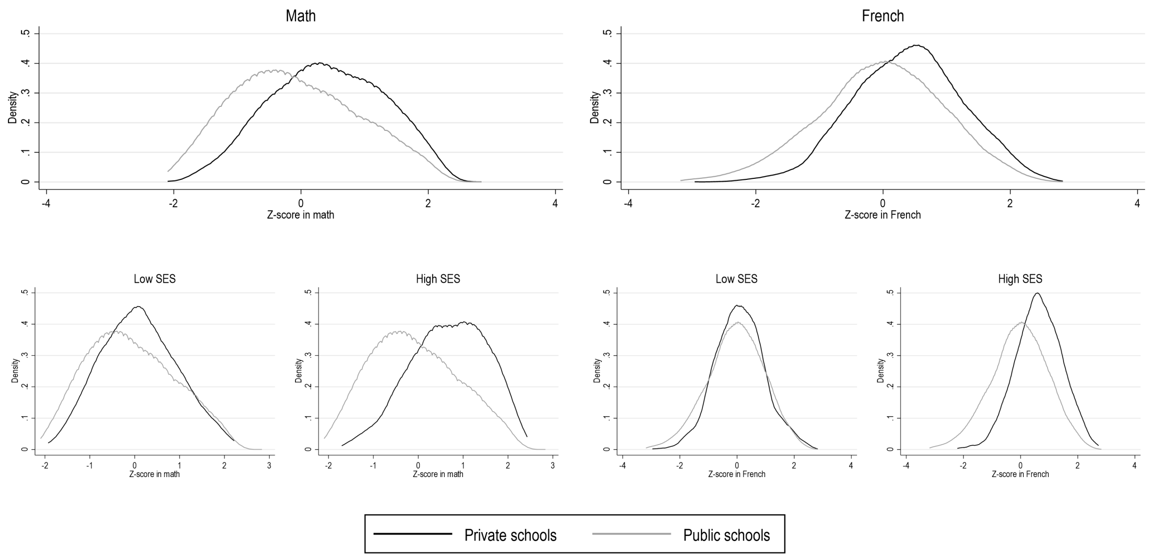
[4]In France, Catholic schools account for 91% of government-funded private lower and upper secondary schools (source: author's calculations based on Cour des comptes, 2023).

from sixth grade (n = 23,958) and those without reported scores in either subject in ninth grade (n = 22,454). Finally, we only consider students enrolled in either public schools or government-funded private schools in ninth grade, resulting in a final sample of 22,441 students.

2.3 Descriptive statistics

We investigate whether school composition plays a role student performance differences between students in public and private school. To do so, we consider the ninth-grade score of students on math and French, which we standardize to have mean of zero and a standard deviation of one.[5] The test scores stem from the French national exam at the end of lower secondary education. As can be seen from the first row in Figure 1, ninth-grade performance differs between students in public and private schools, with students in private schools outperforming students from public schools.[6]

Figure 1: Distribution of the ninth-grade skill scores



Notes: This figure presents the distribution of ninth-grade skill scores in math (left) and French (right). The black line represents the distribution of scores for students in private schools, while the gray line corresponds to students in public schools. In addition, the figure differentiates the score distributions based on SES, highlighting results for both low- and high-SES students.
Source: Panel 2007.

Furthermore, Figure 1 presents a distinction between students from low- and high-SES backgrounds. To make this distinction, we consider the socio-occupational category of the

[5]We standardize the math and French score over the years 2011 and 2012, to make scores between both years comparable. We have test scores for both years to account for students who repeated a grade and were therefore in ninth grade in 2012 instead of 2011.

[6]Students in public schools achieve an average math score of -0.09 SD, compared to 0.41 SD in private schools. A t-test confirms that this difference is statistically significant (p = 0.000). Similarly, the average French score for public school students is -0.04 SD, while private school students score 0.40 SD on average. This difference is also statistically significant (p = 0.000).

students' householder. We use the PCS (Professions and Socio-professional Categories) classification that organizes individuals into four socio-professional tiers based on their occupations and social standing (see Table A.1 in Appendix). First, the highly favored group, which we refer to as high-SES group, includes roles like business owners with ten or more employees, liberal professionals, senior civil servants, and engineers. Second, the favored group, referred to as middle high-SES, encompasses intermediate professions in health and social work, clergy, technicians, and supervisors. Third, the average group, which we translate to the middle low-SES group, features occupations such as farmers, craftsmen, sales employees, and police officers. And fourth, the disadvantaged group includes skilled and unskilled workers, agricultural laborers, and unemployed individuals who have never worked, with a separate category for those whose status is unknown or irrelevant. We refer to this last category as low-SES category. For our analyses, we focus on the two extreme categories to explore the differences in student SES groups. Figure 1 illustrates that students from both low- and high-SES backgrounds attending private schools outperform their counterparts in public schools in math and French.

Table 1 presents descriptive statistics for all variables used in the PSM estimation, distinguishing between public and private schools, with t-statistics shown in the final column. First, we control for sex, distinguishing male and female students, who are equally represented in both school types. High-SES students are proportionally more represented in private (37.14%) than in public school (20.93%). In contrast, low-SES students are more represented in public (35.81%) than in private school (18.86%). Next, parental education is categorized into five levels: (1) tertiary education, (2) general upper secondary education, (3) technical or vocational upper secondary education, (4) vocational education, and (5) no qualification or not reported (NR). Furthermore, significantly fewer students in public schools have fathers with tertiary education (21.77%) compared to private schools (36.73%). Conversely, fathers without qualifications are more prevalent in public schools (32.70%) than in private schools (20.48%). A similar pattern is observed for maternal education. Additional variables include parenthood, immigration background, and number of siblings, all of which show significant differences between school types. Locality size of the student's school is also considered. Last, the analysis includes the student's primary educational trajectory, distinguishing those who attended public versus private primary schools and accounting for grade repetition in primary education. We also control for sixth-grade performance in math and French, assessed via a standardized national test. Table 1 shows private school students significantly outperforming public school students, with average math scores of 0.162 SD and 0.406 SD, respectively, and French scores of 0.171 SD for public schools versus 0.420 SD for private schools.

Table 1: Descriptive statistics by school type

Variables	Public School (%)	Private School (%)	p-value
Socioeconomic characteristics			
Gender			
Girl	51.51%	50.93%	0.500
Boy	48.49%	49.07%	0.500
Socioeconomic status			
High-SES	20.93%	37.14%	0.000
Middle high-SES	17.36%	16.85%	0.423
Middle low-SES	25.90%	27.15%	0.095
Low-SES	35.81%	18.86%	0.000
Mother's educational attainment			
Tertiary education	27.09%	42.79%	0.000
General upper secondary education	6.47%	6.81%	0.430
Technical or vocational upper secondary	11.17%	12.11%	0.088
Vocational education	25.48%	19.60%	0.000
No qualification or NR	25.80%	13.31%	0.000
Father's educational attainment			
Tertiary education	21.77%	36.73%	0.000
General upper secondary education	3.81%	4.15%	0.314
Technical or vocational upper secondary	7.95%	8.51%	0.235
Vocational education	29.78%	24.75%	0.000
No qualification or NR	32.70%	20.48%	0.000
Family type			
Two parents	69.56%	75.92%	0.000
Single mother	13.59%	9.51%	0.000
Single father	1.53%	1.11%	0.025
Blended family	7.03%	5.32%	0.000
Other situations (including NR)	2.44%	1.97%	0.051
Number of siblings	1.931	1.722	0.000
Immigration background			
Parent's born in France	79.84%	85.19%	0.000
At least one foreign-born parent	20.16%	14.81%	0.000

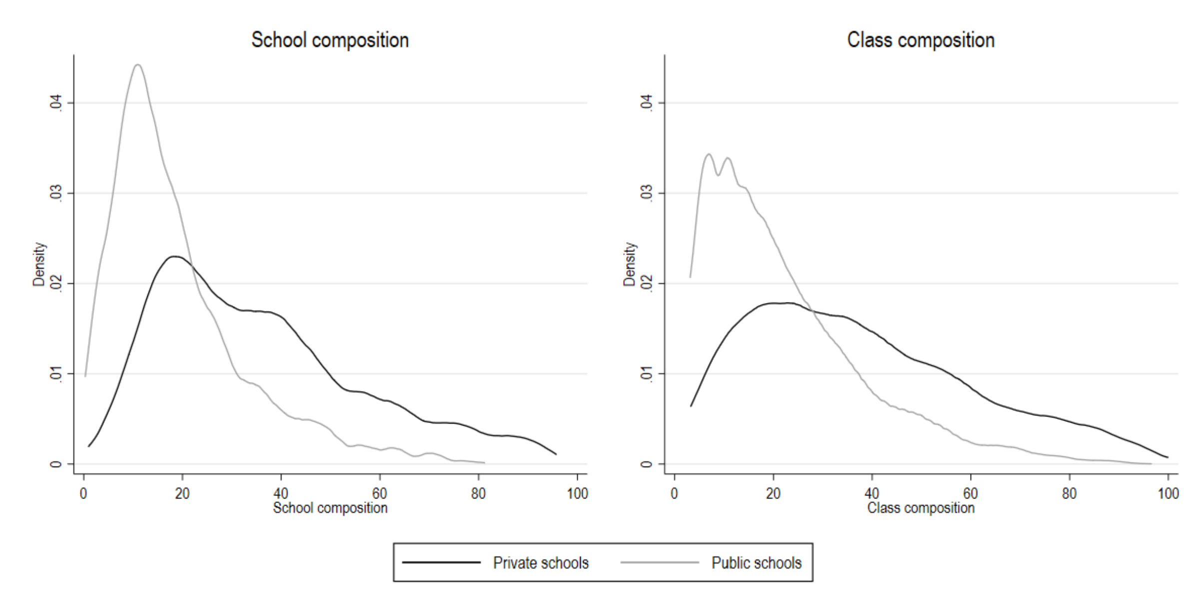
Continued on next page

Variables	Public School (%)	Private School (%)	p-value
School characteristics			
Size of the urban area			
Rural	24.98%	21.38%	0.000
< 5,000 inh	7.82%	7.18%	0.148
[5,000; 10,000] inh	5.96%	5.97%	0.979
[10,000; 20,000] inh	5.26%	5.19%	0.843
[20,000; 50,000] inh	6.28%	5.91%	0.354
[50,000; 100,000] inh	6.65%	7.16%	0.245
[100,000; 200,000] inh	5.59%	5.07%	0.163
[200,000; 2,000,000] inh	22.18%	26.54%	0.000
Paris agglomeration	15.17%	15.53%	0.557
Educational characteristics of the student			
Sector primary education			
Public	89.39%	38.56%	0.000
Private	6.29%	55.86%	0.000
Grade repetition primary education			
No	90.99%	94.78%	0.000
Yes	9.01%	5.22%	0.000
6th-grade test score in math	0.162	0.406	0.000
6th-grade test score in French	0.171	0.420	0.000

Notes: The table presents the weighted summary statistics of our sample. The table presents these statistics for observations in public (left) and private (right) schools. The last columns shows the p-value for the difference between both school types.
Source: Panel 2007.

Next, we present the school composition variable that we consider: the proportion of students from high-SES backgrounds in the school as proxy for the school SES. In addition, we consider a similar variable in the classroom to inspect whether our findings also hold at the classroom level. Figure 2 illustrates the distribution of both variables in public as well as in private school. This figure shows that the composition of both school types significantly differs, with a more advantaged composition in private than in public schools.[7]

Figure 2: Distribution of the school and classroom composition variables

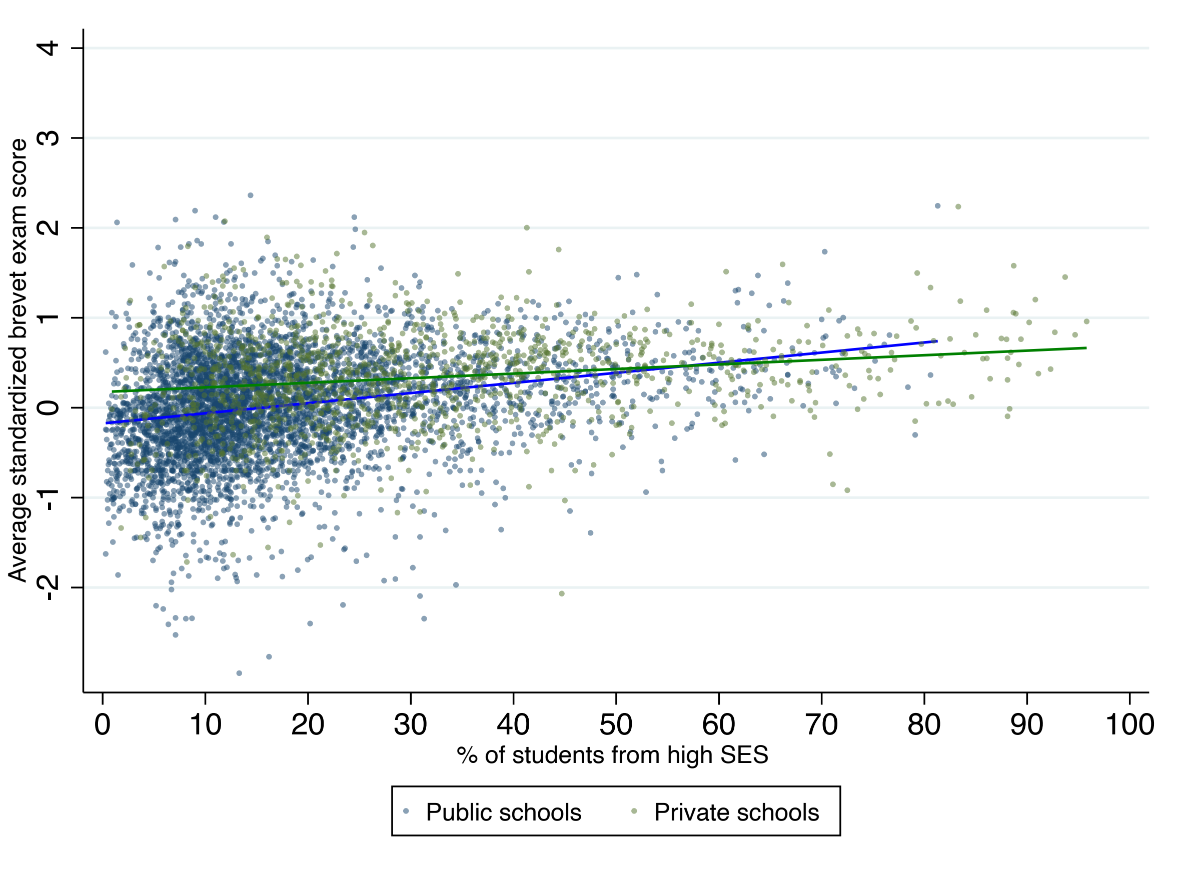


Notes: This figure presents the distribution of school composition (left) and class composition (right). The black line represents the distribution of scores for students in private schools, while the gray line corresponds to students in public schools.
Source: Panel 2007.

As a final part of the descriptives, we visualize the performance of public and private school students on the ninth grade exam score (*'brevet exam'*). Figure 3 illustrates students' exam scores in relation to the percentage of students from a high-SES background within their school. It shows a positive relationship between students' exam scores and the percentage of high-SES students within the school for public and private school students. The figure also suggests that this relationship is stronger for students in public schools (in blue) than for those in private schools (in green), although the differences appear minimal.

[7]The proportion of students from a high-SES background within a school is, on average, 19.75% for public schools, whereas this is 35.92% in private schools. A t-test confirms that this difference is statistically significant (p = 0.000). Similarly, the average proportion of high-SES students within a class is 22.64% in public schools, while this is 37.99% in private schools. This difference is also statistically significant (p = 0.000).

Figure 3: Performance in the brevet exam: public vs. private lower secondary schools



Notes: This figure compares the average standardized brevet exam scores between public (in blue) and private (in green) lower secondary schools, based on the percentage of students from high socioeconomic status (SES) backgrounds. The brevet exam final grade reflects the cumulative performance of students, which includes results from standardized tests as well as continuous assessment scores throughout the academic year.
Source: Panel 2007.

3 Estimation strategy

3.1 Propensity score matching

To evaluate the causal effect of private school attendance on academic achievement, we rely on the well-established potential outcomes framework, originally developed by Roy (1951) and later formalized by Rubin (1974). Since school choice is not random, simple comparisons of mean outcomes between private and public school students may be biased due to selection on observable characteristics. In this context, PSM provides a robust strategy to estimate causal effects by comparing treated and untreated individuals with similar covariate profiles, in the absence of randomized assignment.[8]

[8]PSM has been widely applied in education research, especially in studies assessing the impact of private schooling (e.g., Anand *et al.*, 2009; Azam *et al.*, 2016; Chudgar and Quin, 2012; Nguyen *et al.*, 2006; Sass *et al.*, 2016; Wamalwa and Burns, 2018; Vandenberghe and Robin, 2004). The approach is particu-

Let $D_i \in \{0, 1\}$ denote the treatment indicator, equal to 1 if student i is enrolled in a private school and 0 otherwise. For each student, we define two potential outcomes: $Y_i(1)$, the outcome under private schooling, and $Y_i(0)$, the outcome under public schooling. The observed outcome is thus: $Y_i = D_i Y_i(1) + (1 - D_i) Y_i(0)$ and the individual-level treatment effect is: $\tau_i = Y_i(1) - Y_i(0)$. Since it is not possible to observe both outcomes for the same student, our objective is to estimate the average treatment effect on the treated (ATT):

$$\text{ATT} = E[Y(1) \mid D = 1] - E[Y(0) \mid D = 1]. \tag{1}$$

Identification of the ATT relies on two standard assumptions. First, the conditional independence assumption (CIA) requires that, conditional on a set of pre-treatment covariates, potential outcomes are independent of treatment status. It is captured by the following expression: $Y(0), Y(1) \perp\!\!\!\perp D \mid X$, and implies that all relevant determinants of selection into private schooling are captured by observed covariates. In practice, this means that the propensity score specification must include all variables that jointly influence both treatment assignment and academic outcomes. Second, the common support assumption ensures that for each treated individual, there exists at least one untreated individual with a similar combination of covariates: $0 < \Pr(D = 1 \mid X) < 1$. Provided that the conditional independence and common support assumptions hold, the ATT can be identified as the average difference in expected outcomes between treated and control students with the same propensity score. Formally:

$$\tau_{\text{ATT}} = E[Y(1) \mid p(X), D = 1] - E[Y(0) \mid p(X), D = 0]. \tag{2}$$

The estimation proceeds in two steps. First, we estimate the propensity score using a logistic regression model, where private school attendance is regressed on a comprehensive set of pre-treatment characteristics. These include gender, students' socioeconomic background, mother's and father's educational attainment, family structure, number of siblings, parents' countries of birth, size of the school's urban area, prior enrollment in a private primary school, grade retention during primary education, and academic performance in sixth-grade mathematics. This step captures the selection process into private schools based on observable characteristics. Second, treated students (i.e., those enrolled in private schools in grade 9) are matched with control students using kernel matching, based on the estimated propensity scores. Consistent with standard practice in the literature, we employ an Epanechnikov kernel with a bandwidth of 0.06. The matching is restricted to the region of common support, defined as the overlapping range of propensity

larly useful as students are not randomly assigned to private schools and when numerous covariates must be controlled for (Caliendo and Kopeinig, 2008). It addresses selection on observables by accounting for variables that influence both private school enrollment and outcomes, thereby aiming to reduce potential bias due to unobserved factors (Epple *et al.*, 2016; Spees and Lauen, 2019).

scores between treatment and control groups.

While PSM provides a transparent and intuitive approach to address selection on observable characteristics, it relies on strong identifying assumptions, particularly the CIA. The potential presence of unobserved factors that simultaneously influence school choice and academic performance may still compromise identification. To assess the robustness of our estimates to this threat, we implement two complementary robustness checks (see Section 4.3). First, we use Rosenbaum and Rosenbaum (2002) bounds, which quantify the strength of unobserved confounding required to overturn the statistical significance of our results. Second, we rely on a simulation-based method proposed by Nannicini (2007), which allows us to evaluate the sensitivity of the estimated effects under different scenarios of unobserved heterogeneity, by modelling the bias using an observed proxy variable.

3.2 Propensity score estimation

In Table 2, we present the results of the propensity score logit estimation as the first step in the PSM. This estimation calculates the propensity score, which represents the probability of attending a private school given the covariates. The table indicates that several covariates are significantly associated with the probability of attending a private school. Low-SES students are less likely to attend private schools compared to their high-SES peers, as are students with less-educated parents, those from non-two-parent households, and those with more siblings. Conversely, girls are more likely to attend private schools. Additionally, students who attended private primary schools or achieved higher test scores in primary education are more likely to attend private school in ninth grade.[9]

Table 2: Propensity score logit estimation

Socioeconomic characteristics	
Girl	0.101^{*}
	(0.044)
Socioeconomic status	
High-SES (ref.)	-
Middle high-SES	-0.295^{***}
	(0.071)
	Continued on next page

[9]In addition, we could have included families' aspirations regarding their child's educational track in the propensity score modeling. However, we chose not to retain this variable for two reasons. First, the timing of the question does not precisely match our period of interest: it was asked either in 2007, when all students were in grade 6, or in 2011, when students were in grade 8 or 9, whereas our analysis focuses on private school enrollment in grade 9 in 2011 or 2012. Second, although differences between public and private schools in grade 6 are substantial (for instance, the proportion of students whose parents aimed for a general baccalauréat was 44.71% in public schools versus 53.53% in private schools, with $p = 0.000$), this variable has a high non-response rate (37.67% in public schools and 33.32% in private schools), which limits its inclusion in the analysis. Moreover, it is worth noting that Moulin (2023) includes this variable in his estimations and finds results that are similar to ours regarding the effect of private schooling.

Middle low-SES	-0.084
	(0.070)
Low-SES	-0.532***
	(0.079)
Mother's educational attainment	
Tertiary education (ref.)	-
General upper secondary education	-0.211*
	(0.094)
Technical or vocational upper secondary education	-0.045
	(0.074)
Vocational education	-0.221***
	(0.065)
No qualification or NR	-0.457***
	(0.073)
Father's educational attainment	
Tertiary education (ref.)	-
General upper secondary education	-0.125
	(0.114)
Technical or vocational upper secondary education	-0.120
	(0.090)
Vocational education	-0.062
	(0.073)
No qualification or NR	-0.207**
	(0.077)
Family type	
Two parents (ref.)	-
Single mother	-0.410***
	(0.078)
Single father	-0.136
	(0.218)
Blended family	-0.377***
	(0.105)
Other situations (including NR)	-0.071
	(0.149)
Number of siblings	-0.085***
	(0.019)
At least one foreign-born parent	-0.206**
	(0.065)
School characteristics	
Size of the urban area	
Rural	-0.782***
	(0.105)
< 5,000 inh	-0.629***
	(0.093)
[5,000; 10,000] inh	-0.507***
	(0.096)
[10,000; 20,000] inh	-0.204*
	(0.096)
[20,000; 50,000] inh	0.060
	(0.093)
[50,000; 100,000] inh	0.115
	(0.095)
[100,000; 200,000] inh	0.019
	(0.102)
[200,000; 2,000,000] inh	0.062
	(0.072)

Continued on next page

Paris agglomeration (ref.)	-
Educational characteristics of the student	
Enrolled in a private primary school	3.030***
	(0.048)
No grade retention in primary school	0.137
	(0.099)
6th-grade test score	0.158***
	(0.030)
Constant	-1.586***
	(0.127)
Number of observations	20,309

Notes: Reported coefficients are derived from a logit model estimating the probability of attending a private school in grade 9. 6th-grade test score in the table specifically refers to the mathematics test score. Standard errors are reported in parentheses. Significance levels are indicated as follows: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.
Source: Panel 2007.

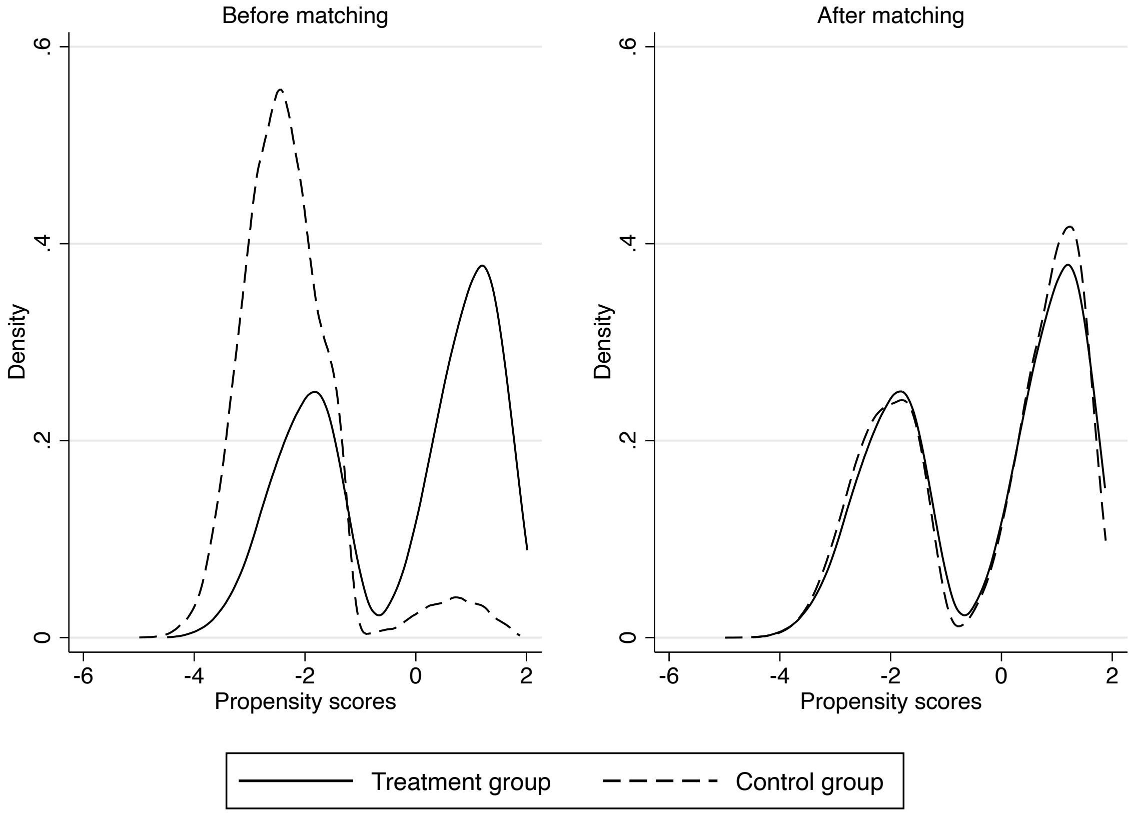
3.3 Propensity score balance and matching quality

We assess balance and matching diagnostics to verify the validity of the propensity score matching process. These diagnostics confirm whether the matching has effectively balanced covariates between treated and control groups, reducing confounding bias.

First, we look at the density balancing plot presented in Figure 4, which visualizes the distribution of the propensity scores before and after matching. The left graph shows that the density score distribution between the treatment and control group visibly differs before the matching procedure. The graph suggests students in the treatment group have on average a higher probability of enrolling in private school, before matching. On the right graph can be seen that this density score distribution is similar for both groups after executing the matching procedure.

Once the matching procedure is performed, it is essential to validate its quality. Table 3 presents various covariate balance indicators before and after matching. Two key metrics are particularly informative. First, the number of statistically significant differences in means between the treatment and control groups, at the 1% significance level, dropped from 18 before matching to 0 after matching. This reduction indicates a substantial improvement in covariate balance. Second, the mean absolute standardized bias decreased significantly, from 15.49% before matching to 2.03% after matching, well below the threshold of 3–5% suggested by Caliendo and Kopeinig (2008). This confirms the high quality of the matching procedure in balancing the covariates across groups. Additionally, other indicators reinforce the success of the matching. The pseudo-R^2 value from the propensity score estimation decreased dramatically from 0.297 before matching to 0.003 after matching, indicating a near-complete elimination of the relationship between the covariates and the treatment assignment. Similarly, the p-value for the joint significance

Figure 4: Density balancing plot.



Notes: This figure illustrates the density score distributions for the treatment and control groups before and after the matching procedure.
Source: Panel 2007.

test of the covariates changed from highly significant ($p = 0.000$) before matching to non-significant ($p = 0.370$) after matching, demonstrating that the covariates no longer explain treatment assignment, indicating successful balancing between the treatment and control groups. Thus, our matching procedure successfully reduced differences in the observed variables between the treatment and control groups, providing confidence in the robustness of the estimates derived from the matched sample.

4 Results

4.1 Main results

We first estimate the average treatment effect on the treated in Table 4, as presented in the first row of the table. The table shows that ninth-grade private school students, on average, score 0.214 SD higher in mathematics compared to their public school counterparts. Similarly, they score 0.170 SD higher in French than their peers in public school.

Table 3: Matching quality

	Before matching	After matching
Number of variables with significant differences in means		
At 1%-level	18	0
At 5%-level	2	3
At 10%-level	1	0
Number of variables with absolute standardized bias		
<1%	2	6
1% until <3%	6	17
3% until <5%	3	4
5% until <10%	4	2
10% until <15%	5	0
$\geq$ 15%	9	0
Mean absolute standardized bias in %	15.49	2.03
Median absolute standardized bias in %	8.44	1.73
Pseudo-R^2 for propensity score estimation	0.297	0.003
p-value of joint significance test	0.000	0.370
Total number of variables	29	29
Treated students off support	8	8

Notes: The propensity score is estimated using a logit model that includes the following variables: gender, students' socioeconomic background, mother's and father's educational attainment, family structure, number of siblings, parents' countries of birth, size of the school's urban area, prior enrollment in a private primary school, grade retention during primary education, and academic performance in sixth-grade mathematics. The logit model results for the propensity score estimation are displayed in Table 2.
Source: Panel 2007.

Table 4: Effect of private school attendance on standardized test scores in grade 9

	Mathematics			French		
ATT	0.214***	0.176***	0.182***	0.170***	0.131***	0.139***
Standard error	(0.022)	(0.025)	(0.024)	(0.020)	(0.025)	(0.023)
School composition	No	Yes	No	No	Yes	No
Classroom composition	No	No	Yes	No	No	Yes
Treated students off support	8	0	35	1	0	38
Number of observations	20,309	20,259	18,699	20,309	20,259	18,699

Notes: The average treatment effects on the treated (ATT) are estimated using PSM with an Epanechnikov kernel and a bandwidth of 0.06. Standard errors are reported in parentheses, and both p-values and standard errors are obtained through bootstrapping with 5000 replications. The variables included in the logit model for estimating the propensity score encompass socioeconomic, school and educational characteristics. The full set of variables used in the propensity score estimation, along with the corresponding logit model coefficients, are presented in Table 2. When estimating the ATT for mathematics, sixth-grade mathematics test scores are included as a control variable, and for French, sixth-grade French test scores are used similarly. Significance levels are indicated as follows: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.
Source: Panel 2007.

In the second column of Table 4, we include school composition in the model to examine whether performance differences between students in private and public school can be explained by the difference of school composition between both school types. We observe that, after including this school composition measure, private school students outperform their counterparts in public school with, on average, 0.176 SD and 0.131 SD in mathematics and French, respectively. This suggests that considering differences in school composition between private and public school only minimally alters the achievement advantage of private school students compared to their public school peers, indicating that other important mechanisms are at play in explaining this effect. We also perform a similar analysis with classroom composition in column 3 and derive a comparable conclusion from this analysis.

These findings are broadly consistent with previous research on the impact of private schooling in France. Moulin (2023) similarly identifies a significant positive effect of private school attendance on ninth-grade test scores using a propensity score matching approach. His results indicate an effect size ranging from 0.203 to 0.222 SD for boys and from 0.138 to 0.198 SD for girls, depending on the subject (math or French), which aligns closely with our estimates. Importantly, by introducing school and classroom composition into the model, our analysis extends this discussion by demonstrating that differences in peer group characteristics only marginally alter the estimated effect of private schooling. This suggests that beyond compositional factors, institutional differences – such as school organization, pedagogical strategies, or resource allocation – may play a central role in explaining the observed performance gap.

4.2 Heterogeneous effects by student socioeconomic status

We next explore heterogeneity in our main result by comparing low- and high- SES students. To ensure that our analysis remains unbiased, we employ a sample-split approach rather than relying on interaction terms (Feigenberg *et al.*, 2023). We present the average treatment effects low- and high-SES students in Table 5. The first four columns present the results for mathematics, while the last four columns display the results for French.

For mathematics, private school students with a low-SES background score, on average, 0.288 SD higher in mathematics compared to their public school counterparts. This differs remarkably from the difference between private and public school students with a high-SES background, which is only 0.094 SD. This suggests that low-SES students benefit the most from attending private schools, yet they remain the most underrepresented group in these schools (cf. Table 1). Table 5 shows a similar finding for French. Low- and high-SES students in private schools outperform their counterparts in French in public schools with 0.265 SD and 0.110 SD, respectively.

Table 5: Effect of private school attendance on standardized test scores in grade 9 by SES

	Mathematics				French			
	High-SES		Low-SES		High-SES		Low-SES	
ATT	0.094*	0.070	0.288***	0.244***	0.110**	0.092	0.265***	0.197***
Standard error	(0.040)	(0.042)	(0.040)	(0.051)	(0.038)	(0.047)	(0.040)	(0.054)
School composition	No	Yes	No	Yes	No	Yes	No	Yes
Treated students off support	2	0	2	3	2	0	2	3
Number of observations	4863	4849	6680	6658	4863	4849	6680	6658

Notes: The average treatment effects on the treated (ATT) are estimated using PSM with an Epanechnikov kernel and a bandwidth of 0.06. Standard errors are reported in parentheses, and both p-values and standard errors are obtained through bootstrapping with 5000 replications. The variables included in the logit model for estimating the propensity score encompass socioeconomic, school and educational characteristics. The full set of variables used in the propensity score estimation, along with the corresponding logit model coefficients, are presented in Table 2. When estimating the ATT for mathematics, sixth-grade mathematics test scores are included as a control variable, and for French, sixth-grade French test scores are used similarly. Significance levels are indicated as follows: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.
Source: Panel 2007.

While the effect for low- and high-SES students differs, the role of school composition also tends to vary for both groups. When taking into account school composition, performance differences in mathematics between private and public school students with a low-SES back remain (0.244 SD). However, the differences in mathematics performance between high-SES students from private and public school disappears, suggesting that school composition completely explains the initial private school effect in mathematics. A similar pattern is observed for French. Considering school composition, high-SES students of private school do not significantly perform better than their counterparts in public school anymore. Low-SES in private students keep their lead to the ones in public school. This implies that attending private schools is especially beneficial for low-SES students and that the initial positive effect of private schooling on high-SES students can be explained the fact that they have a higher proportion of peers with a advantageous background in private schools.

These findings complement previous research on heterogeneity in the effects of private schooling, which shows that private schools tend to be particularly beneficial for initially low-performing students (Abdulkadiroğlu *et al.*, 2011; Angrist *et al.*, 2010, 2013, 2016; Chabrier *et al.*, 2016; Moulin, 2023). Our results extend this literature by showing that students from low-SES backgrounds – a group often less likely to attend private schools – benefit significantly more from private schooling than their high-SES peers. This suggests that private institutions may offer a particularly supportive environment for students facing social disadvantage, not only academic difficulty. The fact that school composition fully accounts for the private school effect among high-SES students, but not among low-SES students, underscores the importance of contextual factors. While high-SES students may already benefit from substantial educational support outside of school, low-SES students appear to experience a real added value from private schooling, potentially through greater academic expectations, discipline, or pedagogical support. These results also raise the question of whether similar gains could be achieved through targeted interventions in the public sector. One key aspect to consider is the role of teachers, which differs significantly between the two sectors. Private schools have more flexibility in shaping their teaching teams, allowing them to ensure better alignment between pedagogical practices and institutional expectations. In contrast, public schools operate within more rigid administrative constraints, which may limit their ability to foster a cohesive and adaptive teaching environment. Granting public schools greater autonomy in the management of their teaching staff – while maintaining rigorous qualification standards – could help create learning conditions that are more conducive to student success.

4.3 Robustness checks

We verify the validity of our results through multiple robustness checks. First, we employ the bounding approach (Rosenbaum and Rosenbaum, 2002), which evaluates the robustness of the estimated effects against potential unobserved biases. Second, we use the simulation approach (Nannicini, 2007), which assesses the sensitivity of the estimated effects to unobserved heterogeneity simulated from observable characteristics.

The sensitivity analysis using the bounding approach, based on the work of Rosenbaum and Rosenbaum (2002), evaluates the robustness of estimated effects in the presence of potential biases caused by unobserved factors that simultaneously influence treatment assignment and outcomes. This methodology quantifies the level of bias a model can tolerate before the estimated effects lose statistical significance. The results presented in Table 6 show that the estimated effects for mathematics and French are generally similar in terms of robustness. However, for high-SES students, the effects appear more sensitive to unobserved biases, as reflected by the slightly lower critical values (Γ) for this group (1.15–1.20 at the 1% significance level in mathematics, compared to 1.70–1.75 for low-SES students). This increased sensitivity can partly be explained by the fact that, as shown in Table 5, the initial effects for high-SES students were smaller and showed relatively weak statistical significance ($p < 0.05$ in mathematics and $p < 0.01$ in French), suggesting that they were more susceptible to being explained away by differences in school composition. The results, at least for low-SES students, seem fairly robust to unobserved heterogeneity. Furthermore, the inclusion of school composition in the models appears to make the estimates more sensitive to unobserved biases, as indicated by the reduction in critical values (Γ) in the sensitivity analysis. This may be explained by the fact that school composition acts as a proxy for unobserved factors, such as the educational environment, which influence both treatment assignment and outcomes.

We employ the simulation approach inspired by Nannicini (2007), which assesses the robustness of estimated effects in the presence of unobserved heterogeneity. This method assumes that an unobserved variable, potentially correlated with both the treatment and the outcomes, shares the same distribution as a specific observed variable. Table 7 thus presents results based on the sensitivity of the effects to such an unobserved variable, simulated from observed characteristics such as gender, parental education level, or family structure. Our ATT estimates remain relatively stable regardless of the type of observed variable used to simulate an unobserved one, and this holds true across the subject studied (mathematics or French) and whether the school composition is included in the model. For instance, for mathematics and low-SES students, the ATT varies only slightly between 0.342 and 0.305 in models without the inclusion of school composition. Similarly, for high-SES students, the ATT fluctuates between 0.124 and 0.131 depending on the variable. mportantly, the estimated effects are consistently close to the baseline results under the "no cofounder" assumption. For example, in mathematics, the ATT for low-SES students without school composition is 0.288, which is close to the range of 0.305–0.342 when unobserved heterogeneity is simulated. This stability in results, regardless of the subject and model specification (with or without accounting for school composition), strengthens confidence in the robustness of the estimated effects, suggesting they are extremely insensitive to the influence of unobserved heterogeneity with a distribution similar to that of the observed variables.

5 Conclusion

Previous research has consistently demonstrated the positive impact of private schooling on student performance, a finding that is also supported by our study. In this paper, we examine whether school composition helps explain these effects. We find that it accounts for only a limited share of the private school advantage – about 15–23% according to our estimates. In addition, we examine SES heterogeneity and find that private schooling is particularly beneficial for students from low-SES backgrounds. However, the low representation of these students in private schools limits their access to these benefits. For high-SES students, we observe initially positive effects, but these are largely explained by the higher concentration of advantaged peers, as the performance gap with public school students disappears once school composition is taken into account.

Taken together, these findings suggest that the benefits of private schooling are not evenly distributed: low-SES students stand to gain the most, yet they are least likely to attend private schools. In contrast, the initial advantage observed for high-SES students appears to be driven primarily by school composition, rather than by any intrinsic quality of private education itself.

To better understand the heterogeneous effects of private schooling across socioeconomic groups, we propose two complementary mechanisms that are consistent with our findings. First, the disappearance of the initial advantage for high-SES students once school composition is controlled for suggests that the performance gap is largely driven by peer effects rather than by intrinsic features of private schools. High-SES students may benefit not so much from private schooling per se, but from being enrolled in socially homogeneous environments where academic engagement is widely shared. Such settings may foster achievement by reinforcing academic norms, reducing classroom disruptions, and creating a climate of high expectations. In this case, the observed advantage reflects selection into more favorable peer groups, not institutional quality. Second, the fact that the private school advantage persists for low-SES students even after controlling for school composition points to other mechanisms beyond peer environment. Private schools may provide a more structured and supportive learning environment that is particularly beneficial for students with limited academic support at home. This may reflect greater organizational autonomy, particularly in the recruitment and management of teachers. Unlike public schools, where teachers are assigned by the central administration, private school principals have the authority to recruit their teaching staff directly. This allows them to build pedagogical teams that are more cohesive in terms of professional commitment, instructional approach, and alignment with the school's educational mission. Such coherence may facilitate the implementation of consistent classroom practices and clearer behavioral expectations, which in turn may help disadvantaged students better engage with the academic and disciplinary framework of the school.

From a policy perspective, our findings raise important considerations regarding the accessibility of private education for disadvantaged students. If private schools contribute to reducing academic inequalities for low-SES students, mechanisms to support their enrollment – such as targeted scholarships or financial aid – could be explored. However, rather than focusing solely on expanding access to private schools, it is also crucial to investigate whether certain institutional features of private education – such as pedagogical practices, teacher management, or school-level autonomy – could be adapted within the public sector. Future research should examine these mechanisms more closely, including specific instructional approaches, differences in school climate, or variations in teacher expectations, and assess whether similar effects can be replicated through targeted reforms in public schools. Such efforts could provide valuable insights into how to foster educational equity without relying exclusively on private school expansion.

Table 6: Sensitivity analysis – bounding approach

	Mathematics				French			
	High-SES		Low-SES		High-SES		Low-SES	
1.00	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1.25	0.127	0.492	0.000	0.000	0.040	0.251	0.000	0.000
1.50	0.968	0.999	0.000	0.012	0.890	0.990	0.000	0.103
1.75	0.999	1.000	0.018	0.305	0.999	0.999	0.077	0.688
2.00	1.000	1.000	0.271	0.839	1.000	1.000	0.527	0.978
Critical values								
1%	1.15-1.20	1.05-1.10	1.70-1.75	1.45-1.50	1.20-1.25	1.10-1.15	1.60-1.65	1.35-1.40
5%	1.20-1.25	1.10-1.15	1.80-1.85	1.55-1.60	1.25-1.30	1.15-1.20	1.70-1.75	1.45-1.50
10%	1.20-1.25	1.15-1.20	1.85-1.90	1.60-1.65	1.25-1.30	1.20-1.25	1.75-1.80	1.45-1.50
School composition	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Results were obtained using Rosenbaum and Rosenbaum (2002) bounds to evaluate sensitivity to unobserved heterogeneity. The top part of the table displays the probabilities at which estimated effects lose statistical significance as the level of unobserved bias (Γ) increases. The bottom part lists the critical Γ thresholds at which effects become non-significant at the 1%, 5%, and 10% levels. Higher Γ values indicate greater robustness, meaning that stronger unobserved bias would be required to invalidate the results. The variables included in the logit model for estimating the propensity score encompass socioeconomic, school, and educational characteristics. The full set of variables used in the propensity score estimation, along with the corresponding logit model coefficients, are presented in Table 2. When estimating the ATT for mathematics, sixth-grade mathematics test scores are included as a control variable, and for French, sixth-grade French test scores are used similarly.
Source: Panel 2007.

Table 7: Sensitivity to unobserved heterogeneity – simulation approach

	Mathematics				French			
	High-SES		Low-SES		High-SES		Low-SES	
No cofounder	0.094	0.070	0.288	0.244	0.110	0.092	0.265	0.197
Gender - Girl	0,124	0,091	0,342	0,295	0,135	0,117	0,310	0,242
Mother's educational attainment - Tertiary education	0,116	0,080	0,329	0,284	0,123	0,103	0,295	0,230
Father's educational attainment - Tertiary education	0,121	0,086	0,342	0,295	0,129	0,109	0,311	0,242
Family types - Two parents	0,119	0,086	0,332	0,288	0,131	0,112	0,302	0,238
Parents' born in France	0,123	0,090	0,322	0,279	0,134	0,115	0,292	0,229
Size of the urban area - Paris agglomeration	0,126	0,094	0,334	0,287	0,133	0,115	0,305	0,238
Enrolled at least once in a private primary school	0,131	0,072	0,305	0,211	0,170	0,115	0,307	0,211
Grade repetition in primary school	0,121	0,089	0,335	0,287	0,132	0,113	0,301	0,233
School composition	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The reported results represent the ATT, estimated using a simulation approach (see Nannicini, 2007). The number of replications is 5,000. The variables included in the estimation encompass socioeconomic, school and educational characteristics (see Table 2). When estimating the ATT for mathematics, sixth-grade mathematics test scores are included as a control variable, and for French, sixth-grade French test scores are used similarly.
Source: Panel 2007.

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Appendix

Table A.1: Nomenclature for Socio-Professional Categories

PCS	PCS Code
High-SES	
Business owner with ten or more employees	23
Liberal profession	31
Senior civil servant	33
Teacher and equivalent	34
Information, arts, and entertainment professional	35
Administrative and commercial manager in a company	37
Engineer - technical manager in a company	38
Primary school teacher and equivalent	42
Middle High-SES	
Intermediate profession in health and social work	43
Clergy, religious personnel	44
Intermediate administrative profession – public sector	45
Intermediate administrative and commercial profession – private sector	46
Technician	47
Foreman, supervisor	48
Retired executive or intermediate profession	73
Middle Low-SES	
Farmer	10
Artisan	21
Shopkeeper and equivalent	22
Civil employee, service agent – public sector	52
Police officer and military personnel	53
Administrative employee in a company	54
Sales employee	55
Personal service worker	56
Retired farmer	71
Retired artisan, shopkeeper, or business owner	72
Low-SES	
Skilled worker	61
Unskilled worker	66
Agricultural worker	69
Retired employee or worker	76
Unemployed person who has never worked	81
Person without professional activity	82
Not specified (unknown or not applicable)	99

Source: DEPP – MESR.