More harm than good? Sorting effects in a compensatory education program

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Abstract

We provide evidence that school-based compensatory education policies create sorting effects, by analyzing a French program, which targeted low-achieving and socially disadvantaged junior high schools. We use geocoded original data, and a regression discontinuity framework to show that the program decreases the individual probability to attend a treated school, and symmetrically increases the probability to attend a private school. The effects are driven by pupils from high socio-economic backgrounds, resulting in an increase in social segregation across schools.

Keywords: Education, Education Policy, Sorting, Treatment Effect Model, Regression Discontinuity

JEL classification: I24, I28, C21

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Introduction

Compensatory education policies aim at offsetting educational inequalities between socially and academically disadvantaged children, and more advantaged ones. These policies first appeared in the 1960's in developed countries, when mass schooling and equal access to education were found to be insufficient to ensure equal opportunity. The fundamental idea is to provide some sub-population with additional resources in order to achieve equal opportunity through unequal treatment. Such education programs traditionally target schools in socially and academically deprived areas. For that reason, they are referred to as place-based (or school-based) programs, as opposed to individual-based ones. Such programs exist worldwide and are widely used to try to tackle underachievement; Title I of the Primary and Secondary Education Act or Harlem Children's Zone in the US, P-900 in Chile, Education Priority Areas or Excellence in Cities in the UK, "*Zone d'éducation prioritaire*" (ZEP) or "*Réseaux d'éducation prioritaire*" in France are examples, among many, of such policies. These programs usually represent a significant part of public spending in education. The sole Title I program, for instance, represents around 14 billion dollars per fiscal year. In France, compensatory education corresponds to about 1 billion euros each year. In both cases, the additional spending over the number of recipients represents about 10% of the annual spending per pupil.

Providing underprivileged schools with (sufficiently) more resources is expected to improve pupils' performance and, ultimately, to close the educational gap.[1] The empirical evidence, however, is mixed. Some programs, notably when they intervene very early in primary or in pre-primary education, have both positive and somewhat large effects on pupils' performance (Dobbie and Fryer, 2011; Shapiro and Moreno Treviño, 2004; Tokman, 2002). But other place-based compensatory education programs have limited (Borman and D'Agostino, 1996; Chay et al., 2005; Machin et al., 2004, 2010; Bénabou et al., 2009; Caille et al., 2016), or even negative results (van der Klaauw, 2008; Leuven et al., 2007; Beffy and Davezies, 2013).

Evaluating compensatory education programs is a complex task since two effects are likely to bias the analysis. First, by definition, such programs target disadvantaged populations.

[1]Compensatory education policies were originally not meant to last. In France, for instance, additional resources provided to ZEP schools were supposed to end once the achievement gap closed: "If a sustained action over several years is needed, it would not be advisable to consider permanent assistance [...]" (Minister of National Education, Circular No. 81-536 clarifying the objectives of "*zones prioritaires*," December 1981, authors' translation).

Selection into the program is often made at the school level, on the basis of social and academic criteria (location in deprived areas, poor academic achievement, large proportion of pupils from ethnic minorities, or from disadvantaged social backgrounds, etc.). A second source of bias comes from the fact that compensatory education programs usually target schools and not individuals directly. And because individuals can choose which school to attend, it is difficult to estimate the individual effect of the program on pupils, because one need to account for school and location choices. Individuals may select themselves into (or out of) the program by choosing (or avoiding) a school that benefits from it. We will refer to this second source of bias as a sorting effect. So far, this second type of bias has not been properly accounted for in the litterature.

One main limit of the literature on compensatory education is that it usually focuses on schools and ignores individual adjustments to school-based policies. Yet endogenous sorting of individuals across schools or across neighbourhoods is expected to significantly modify place-based policies impacts. A growing theoretical and empirical literature shows first that individuals do adjust to a change in public good provision by moving or changing schools (Ferreyra, 2007; Hsieh and Urquiola, 2006; Urquiola, 2005; Urquiola and Verhoogen, 2009), and second, that they incorporate these adjustments in their decisions (Epple et al., 2001). In this paper, we want to explore the idea that individual responses to school-based policies may mitigate their expected impacts (Nechyba, 2003; Pop-Eleches and Urquiola, 2013) and lead to adverse effects.

The expected impact of school-based programs on neighbouring families school choices is not clear. On one hand, treated schools may become more attractive, because they benefit from additional resources (Dinerstein and Smith, 2015). Some families may thus try and enroll their child(ren) at these particular schools. On the other hand, the program may signal treated schools as low-achieving and socially disadvantaged. In this case, some families may try and avoid such schools, because they infer low school quality (Figlio and Lucas, 2004; Hastings and Weinstein, 2008), or low peer quality (Rothstein, 2006), or anticipate bad reputation effects (MacLeod and Urquiola, 2012, 2015). Moreover, families from different socioeconomic backgrounds are expected to value this new information on school attributes differently (Burgess et al., 2015; Hastings et al., 2009). In the French context, the first scenario is unfortunately not the more credible. Although no one has studied individual school choice in this context before, there is evidence that compensatory education schools' composition changed, suggesting that some families tend to avoid treated schools (Bénabou et al., 2004; Beffy and Davezies, 2013; Maurin, 2004).

In this paper, we analyze the impact of place-based compensatory education on individual sorting across schools. To our knowledge, this is the first attempt to evaluate sorting effects due to a compensatory education program. To do that, we consider the specific case of the French "*Réseaux ambition réussite*" (RAR) program, which targeted very low-achieving and socially disadvantaged junior high schools between 2006 and 2011. In a first part, we assess the causal impact of the program on families school choice by using an original geocoded individual data set and a regression discontinuity identification strategy. More precisely, we use an exogenous eligibility scheme of schools into treatment. To be eligible, schools had to enroll 67% of pupils from low socioeconomic status (SES) backgrounds, and 10% of repeaters. We ask whether living in the vicinity of a RAR school affects individual school choice, by comparing pupils whose closest school is just above versus just below the eligibility criteria. We find that living near a RAR junior high school decreases the probability to attend the closest school by 20 to 38 percentage points, and symmetrically increases the probability to go to a private school, for pupils living near a school just above the eligibility thresholds. We also find that pupils from high socioeconomic status backgrounds are more likely to attend a private school when they live near a RAR junior high school. Furthermore, sorting effects are higher for children of teachers. These findings are in line with a theoretical model which predicts that wealthier families, and families with high preference for school quality react more than others to the RAR signal. In a second part, we discuss the policy implications. They are twofold. First, the program increases social segregation across schools. Second, sorting effects challenge the usual identification strategies of school-based policies causal impact on pupils' academic achievement. We find no significant effect of the program on pupils' academic performance, once endogenous sorting is taken into account.

The paper is organized as follows. We briefly describe the French education system and the RAR program in the next section. In section 2, we propose a simple theoretical model to account for sorting effects. Section 3 presents the data. Section 4 investigates the effect on individual school choice of the RAR program. Then section 5 discusses the implications of our results for the evaluation of place-based education policies, and analyzes the effect on pupils' academic achievement. Section 6 presents robustness checks. Section 7 concludes.

1 A brief description of the French education system

In France, education is compulsory for children aged 6 to 16. The French school system consists of 5 years of primary school (ages 6 to 10), then 4 years of lower secondary education in junior high school, called "*collège*" (ages 11 to 14), and 3 years of upper secondary education in high school, called "*lycée*" (ages 15 to 17).

At the end of junior high school (in grade 9), French pupils take a standardised national examination, called "*Brevet*". It consists of a written exam covering three subjects: French, Mathematics, and History-Geography (including Civics), and a continuous assessment, measured as the general average of grades obtained in all subjects during the 9th grade's school year. Passing the "*Brevet*" is not a prerequisite for continuing with higher secondary schooling, but almost all 9th graders take this exam.

French primary and secondary education is based on a catchment area system; each pupil is assigned to a public school according to where she lives. Junior high school catchment areas are delimited at the local level by the "*département*" ("*conseil général*"), and each area contains only one junior high school. The catchment area school represents families' default school options. Families also have two outside options: they can either send their child to a private school, or they can ask for another public school through a special dispensation. Most private schools are largely subsidised by the state and follow the same curriculum as public schools (except for religious instruction),[2] so they constitute a commonly used outside option. Dispensations, on the other hand, are granted by the regional education authority director on the basis of (in order of priority) medical reasons, scholarship, siblings, distance, and special academic tracks. Pupils living in the catchment area have priority, and dispensations are only accorded if all places were not fulfilled by them.[3]

The 2006 French compensatory education reform created a new structure called the "ambition success" networks ("*Réseaux Ambition Réussite*" or RAR). The program targeted the most disadvantaged junior high schools. Each network consisted of one junior high school,

[2]Most private schools in France are Catholic schools.

[3]The catchment area system was partly relaxed in 2007. This was supposed to give families more freedom in school choice. The increasing number of dispensation demands resulted in a decrease in the size of RAR schools (Fack and Grenet, 2013). However, as long as there is no more dispensation demands above or below the eligibility thresholds (see below) in the absence of the RAR program, this does not constitute a confounding factor for our analysis.

and of the primary and infant schools of the catchment area. The network was managed by an executive committee, composed of the head of the junior high school, the heads of the elementary and infant schools, and the Ministry of National Education inspector responsible for the schools district. The aim of these networks was to build or reinforce the relationships between teachers within the network in order to tackle underachievement in these schools. To achieve this goal, each network had to define an educational project through a four- to five-year contract. Each project had to be built up to reinforce individualised support, develop partnerships with cultural or sports organisations, and strengthen relationships with parents. To reach these objectives, RAR junior high schools were provided with additional resources in order to finance $1\ 000$ extra teachers and $3\ 000$ teaching assistants. The extra teachers, whether primary or secondary, were recruited on the basis of individual RAR projects. Their classroom teaching hours were limited to a halftime service so that they could organise tutoring groups and individual homework assistance, manage teaching assistants, and supervise the relationships with parents. Teaching assistants were in charge of helping pupils both inside and outside the classroom. These additional resources were supposed to enable schools to reduce class size.

The selection of junior high schools in RAR was made on the basis of objective criteria, which were evaluated at the national level during the 2004/2005 school year. These criteria were the proportion of children from low socioeconomic status backgrounds in the school and the proportion of pupils who, upon entering 6th grade, had repeated two grades. More precisely, junior high schools had to have at least 67% of low SES pupils[4], as well as at least 10% of 6th-grade-level pupils having repeated twice or more, to become eligible to the program.[5] These thresholds were arbitrarily defined so that selected schools would represent the 5% most socially and academically disadvantaged pupils. The list of eligible schools was approved by the Minister of National Education. Then some further adjustments were made, and some schools that were eligible did not enter the treatment, whereas some schools below the thresholds did enter it.

The additional cost of RARs has been estimated at nearly 325 million euros for the budget year 2008. It corresponds to about 811 additional euros per pupil, approximately 10% of the

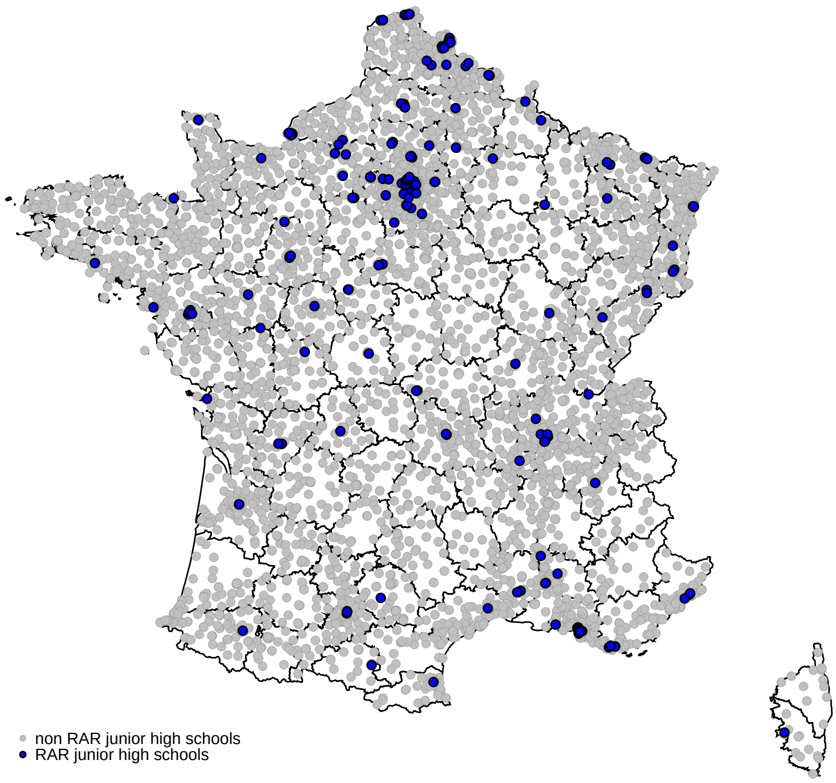
[4]Low SES pupils were defined as children of blue-collar workers, of retired blue-collar workers, of retired white-collar workers, or of the unemployed.

[5]Some regional education authorities used an additional measure of pupils' achievement at the beginning of 6th grade. But since this measure was not available in every school, it is not used in this analysis.

annual spending per junior high school pupil. 90% of the extra cost corresponds to the funding of teachers and assistants.

In total, 249 public junior high schools entered the RAR program from the beginning of the 2006 school year. Four additional public schools entered in 2007. These schools were located all over the country, mainly in urban areas. Figure 1 shows the repartition of public junior high schools in mainland France.[6]

Figure 1 – Map of public junior high schools in the sample



Source: MEN-MESR DEPP, FAERE 2006 and 2007

The main objective of the program was to significantly increase the supervising staff in a small number of treated schools. If uniformly distributed among the 249 schools, additional positions would represent about 4 extra teachers, and about 12 extra teaching assistants per school. But because there was no specific follow-up of these schools after the beginning of

[6]Overseas "*départements*"' are excluded from the analysis for two reasons. First, the proportion of RAR schools is much higher in overseas "*départements*" than in mainland France, meaning that the eligibility criteria may poorly capture whether they entered the program or not. Second, schools in overseas "*départements*" are often badly geocoded.

the program, the actual increase in the number of teachers and teaching assistants needs to be estimated. In a preceding study, Beffy and Davezies (2013) show that the increase in the number of teaching hours per pupil, and the decrease in class size were not very significant and were less than expected if resources had been uniformly distributed across schools. The authors also find that the proportion of teachers having the highest secondary school teaching certification (*agrégation*) decreased, and that the proportion of teachers more than 55 years old increased.[7] Therefore, the impact of the program on pupils' performance is expected to be mainly driven by an increase in the supervising staff, but, though positive, it is not expected to be large.[8]

Another objective of the RAR program was to break the relatively bad reputation of low-achieving schools, by creating an ambitious and successful environment in treated schools. This first translated into the name of the program, which was changed from "compensatory education zones" to "ambition success networks". Second, trying to prevent families from avoiding treated schools was mentioned in many RAR schools contracts. Some school headmasters were so worried about such strategies that they preferred not to publicize the fact that the school was RAR. Our results will show that the program did not make treated schools more attractive, and that a negative signal scenario is compatible with our findings.

2 Theoretical mechanisms

To better understand the mechanisms at stake, let us consider a simple theoretical model. Following Friesen et al. (2012) and Moretti (2011), let us define a Bayesian learning model in which each family chooses a junior high school on the basis of expected school quality. Quality q_j of each school j is unobserved, but families hold prior beliefs $\pi(q_j)$ on school quality. This prior also depends on school observed characteristics, such as whether it is a private or public school, past average score at the national exam, pupils' social backgrounds, teachers characteristics, etc. To simplify notation, let us assume that prior beliefs implicitly depend on observed characteristics.

[7] Other papers (Hanushek et al., 2004; Prost, 2013) show that teachers mobility is higher in socially and academically disadvantaged schools.

[8] See Jepsen and Rivkin (2009) for an investigation of the effect of both class size reduction and related changes in teacher quality.

For sake of simplicity, families' utility function is assumed to be additively separable between q_j and the consumption good c:

$$U(q_j, c, \theta) = \theta \times v(q_j) + u(c)$$

with v and u increasing and concave functions, and $\theta > 0$ a parameter of preference for school quality. Families' income is denoted R, and the price of the consumption good is normalized to 1. Families are heterogeneous in (θ, R), meaning that some families are wealthier and/or more concerned about school quality than others.

Let us assume that families have to choose between the nearest public school (called school A) and another private school B. Families have to pay fees p_B (the same for all families) to enroll their child in school B. Because B is private, it cannot be RAR.[9] With the RAR program, families receive a dichotomous signal S_A on q_A. Let $S_A = 1$ if school A is RAR, and 0 otherwise.

The RAR status is common knowledge, and families update their beliefs about school A's quality using this information, with a prior belief $\mathbb{P}(S_A = 1|q_A)$ decreasing in q_A. The Bayesian update on the distribution of q_A given $S_A = s$ is:

$$\pi_s(q_A) := \frac{\mathbb{P}(S_A = s|q_A) \times \pi(q_A)}{\mathbb{E}_\pi(\mathbb{P}(S_A = s|q_A))}$$

A RAR school gets additional resources δ, which may increase ex-post school quality: $v(\tilde{q}_A) = v(q_A) + \delta$, with $\delta > 0$. Families do not perfectly observe δ, and we assume that they have prior belief $\widetilde{\pi}(\delta)$ on additional resources. Let $\overline{\delta} = \mathbb{E}_{\widetilde{\pi}}(\delta)$ denote expected additional resources.

The expected utility of going to school A is:

$$\begin{cases} \theta \mathbb{E}_{\pi_1}(v(q_A)) + \theta\overline{\delta} + u(R) & \text{, if } A \text{ is a RAR school,} \\ \theta \mathbb{E}_{\pi_0}(v(q_A)) + u(R) & \text{, if } A \text{ is not a RAR school.} \end{cases}$$

Let π' denote prior belief on the quality of private school B. The expected utility of going to B is:

$$\theta \mathbb{E}_{\pi'}(v(q_B)) + u(R - p_B).$$

[9] We could alternatively consider that school B is another high quality public school, which is thus not part of the RAR program. In this case, p_B would be the transportation, or moving, or administrative costs to go to this school.

Depending on their beliefs on school quality, families adapt their school choice to incorporate the information given by the RAR treatment. Let us denote $\Delta\mathbb{E}(v) = \mathbb{E}_{\pi_0}(v(q_A)) - \mathbb{E}_{\pi_1}(v(q_A))$ the difference in school A's ex-ante expected quality, depending on its RAR status. Because $\mathbb{P}(S_A = 1|q_A)$ is decreasing in q_A, it follows that $\mathbb{E}_{\pi_1}(v(q_A)) \leq \mathbb{E}_{\pi_0}(v(q_A))$, so that $\Delta\mathbb{E}(v)$ is positive.[10]

The effect of the RAR policy on families' school choices depends on two key quantities: $\Delta\mathbb{E}(v)$ and $\overline{\delta}$ (see Appendix A for a complete analysis of the model's theoretical predictions). The first quantity, $\Delta\mathbb{E}(v)$, is related to the strength of the RAR signal on ex-ante school quality, and the uncertainty about ex-ante school quality. If assignment to the RAR program was random, then families would not use the RAR status to infer something about ex-ante school quality, and $\Delta\mathbb{E}(v)$ would be equal to zero. Similarly, if families were able to perfectly observe ex-ante school quality, then the RAR signal would be uninformative, and $\Delta\mathbb{E}(v)$ would be zero. But if school quality is unobserved, and since the RAR program targets low-quality schools, families update their beliefs, and $\Delta\mathbb{E}(v)$ is positive. The second parameter driving the equilibrium is $\overline{\delta}$, i.e. beliefs about the program's efficiency (in terms of expected utility). If families are sufficiently optimistic about the program's efficiency (i.e. $\overline{\delta}$ is large), and/or sufficiently informed about school quality (i.e. $\Delta\mathbb{E}(v)$ is small), then the RAR program increases enrollment in treated schools, and enrolled families are wealthier, and more concerned about school quality (*caeteris paribus*), with respect to families who always choose the nearest public school. On the contrary, if families are not sufficiently optimistic about the program's efficiency (i.e. $\overline{\delta}$ is small), and/or not sufficiently informed about school quality (i.e. $\Delta\mathbb{E}(v)$ is large), then the RAR program may have detrimental consequences in terms of social segregation: enrollment in treated schools decreases, because wealthier and more concerned families choose the private sector (and are willing to pay a price p_B for that).

The empirical results in Section 4 are compatible with the second-case scenario: parents tend to avoid treated schools, and high SES families and families with one parent being a teacher are more likely to avoid treated schools than other families, increasing social segregation across schools.

[10]Because $-v(q_A)$ and $\mathbb{P}(S_A = 1|q_A)$ are both decreasing with q_A, then $\mathbb{C}ov_{\pi}(v(q_A), \mathbb{P}(S_A = 1|q_A)) \leq 0$, and $\mathbb{E}_{\pi_1}(v(q_A)) \leq \mathbb{E}_{\pi}(v(q_A)) \leq \mathbb{E}_{\pi_0}(v(q_A))$.

3 The data

To analyze the effect of the program on pupils' school choice and academic achievement, we use exhaustive micro-level data provided by the statistical service of the French Ministry of Education, both at the pupil and school levels.

First, we use annual exhaustive individual data sets of French secondary education pupils (called "*fichiers anonymisés d'élèves pour la recherche et les études*" or FAERE). We focus on pupils entering junior high school (6th grade) in 2006 and 2007, that is, the first two cohorts of pupils affected by the RAR program, and we are able to track them for five years. Pupils entering 6th grade later are not taken into account for two reasons; first, at the time of this study, their scores at the "*Brevet*" national exam and their situations five years after entering 6th grade were unknown; second, the program may have had long term effects on location and primary school choices, which would bias our analysis (see Section 6). These data come from administrative sources and gather some information on pupils: we observe their sexes, ages, origins, their family backgrounds through their parents' occupations, and whether or not they benefit from a scholarship. These data were matched with the exhaustive "*Brevet*" national exam data set.[11] The situation of pupils just after the end of junior high school is also observed. We know which junior high schools they attend in 6th grade, whether these are public or private schools, and whether these are RAR schools or not. We observe which primary schools they attended the preceding year, with their exact geographic locations.

A second source of data comes from an exhaustive data set at the school level in which we observe every mainland France public junior high school with their exact geographic location.[12] For each of these schools, we observe the proportion of low SES pupils[4] and the proportion of repeaters when entering 6th grade as evaluated during the 2004-2005 school year, i.e. we perfectly observe whether or not each junior high school was eligible to the RAR program.

Combining those two data sets, we are able to define each pupil's closest public junior high school as the closest to his or her primary school, using the smallest (Euclidean) distance.

[11]For every cohort, we observe two consecutive "*Brevet*" sessions, so that the results of pupils who repeated one grade during junior high school are observed. When a pupil was present in both sessions, we only kept the first one.

[12]In the school-level data-base, we only consider public junior high schools. However, we do observe pupils enrolled at a private school in the individual-level data-base so that the private sector is not excluded from the analysis.

Because we don't know the exact location of pupils' homes, we approximate their location by the location of their primary school. Note that we also don't know their catchment area junior high school; instead, we consider the closest public junior high school to their primary school. Because more than half of pupils are enrolled at the closest school to their primary school (cf. Table 1), this is a good proxy for families' default school option.

In the following, we will consider two treatment variables. The first one is whether pupils live "in the vicinity" of a RAR junior high school, i.e. the closest junior high school to their primary school is RAR. The second one is whether pupils are enrolled at a RAR junior high school in 6th grade. Because we observe pupils every schooling year, we could have considered being enrolled at a RAR school the whole time of lower secondary education as an alternative variable. However, the vast majority of pupils (more than 80%) attend the same school during all lower secondary education. Moreover, the results are similar when we consider this alternative variable.

We restrict our sample to pupils living in mainland France, and we thus observe 1 098 636 individuals, with 531 729 entering 6th grade in 2006 and 566 907 in 2007 (see Table 1). Among them, 45 376 are living in the vicinity of a RAR junior high school, and 28 517 are enrolled at a RAR junior high school; that is, 3% of the sample. More than 50% of pupils are going to their closest public junior high school, while 27% are attending another public school. Around 20% of 6th grade pupils are attending a private school. Among pupils living near a RAR junior high school, 41% are attending the closest (RAR) public junior high school, 40% are going to another public school, and 19% are attending a private school.

A first descriptive statistics analysis shows that pupils attending a RAR junior high school in 6th grade have poorer academic outcomes than other pupils. 69% of them pass the "*Brevet*" national exam four to five years after entering 6th grade, compared to 87% of non RAR pupils. On average, RAR pupils get a total exam score of 8 over 20, compared to 11 over 20 for non RAR pupils. At the end of junior high school, 43% of pupils who entered a RAR school in 6th grade continue in a general upper secondary education track ("*second cycle général ou technologique*"), compared to 62% of non RAR pupils. Because the RAR program aimed at targeting socially and academically disadvantaged pupils, such differences are not surprising and may come from the fact that RAR pupils are a population that is not directly comparable to non RAR pupils (see left part of Table 2). For instance, pupils attending a RAR junior high school in 6th grade are older, on average, than non RAR pupils (0.21 year older, that is, 2

Table 1 – Description of the sample

	Frequency	Percentage
Cohort		
2006	531,729	48.4
2007	566,907	51.6
Nearest school is RAR		
No	1,053,260	95.9
Yes	45,376	4.1
Enrolled in a RAR		
No	1,070,119	97.4
Yes	28,517	2.6
Enrolled in nearest school		
No	515,062	46.9
Yes	583,574	53.1
Enrolled in another public school		
No	807,240	73.5
Yes	291,396	26.5
Enrolled in a private school		
No	874,970	79.6
Yes	223,666	20.4
Total	1,098,636	100.0

Source: MEN-MESR DEPP, FAERE 2006 and 2007

months and a half older). On average, they come more often from a low SES background[4], and they benefit more often from a scholarship than other pupils (47 percentage points more).

Moreover, living near a RAR junior high school is certainly not exogenous either. Pupils living near a RAR junior high school are very different from other pupils according to their observable characteristics (see right part of Table 2); on average, they are a bit older than other pupils when entering 6th grade (11.22 years old compared to 11.10 for other pupils, or about 1.5 month older), they are less often born French (95% of them compared to 98% of other pupils), they come much more often from a disadvantaged social background (56% of them compared to 33%), and they benefit more often from a scholarship (48% of them compared to 20% of other pupils). Furthermore, pupils living near a RAR junior high school live in municipalities where the median households revenue is about $4,500$ euros smaller on average than in other pupils' municipalities, where the unemployment rate is about 1 point higher and where the population density is about $2,000$ inhabitants per square kilometer higher than in other pupils' municipalities (Table 8 in Appendix C).

Of course, such differences are not surprising, since the RAR program was aimed at targeting pupils in socially disadvantaged schools. But these differences highlight the fact that a naive comparison between pupils affected by the RAR program and other pupils would lead to a selection bias, since they would be very different populations even in the absence of the program.

Table 2 – Individual characteristics in the sample

Individual characteristics of	pupils not enrolled in a RAR	pupils enrolled in a RAR	Test (p-value)	pupils not living near a RAR	pupils living near a RAR	Test (p-value)
Male	0.50	0.49	0.002	0.50	0.49	0.001
	(0.001)	(0.003)		(0.001)	(0.002)	
Age at 6th grade	11.10	11.31	<0.001	11.10	11.22	<0.001
	(0.001)	(0.005)		(0.001)	(0.005)	
Born French	0.98	0.93	<0.001	0.98	0.95	<0.001
	(0.000)	(0.005)		(0.000)	(0.003)	
Low SES	0.33	0.72	<0.001	0.33	0.56	<0.001
	(0.002)	(0.007)		(0.002)	(0.009)	
Scholarship	0.20	0.67	<0.001	0.20	0.48	<0.001
	(0.001)	(0.008)		(0.001)	(0.009)	
Nbr obs	1,070,119	28,517		1,053,260	45,376	

Notes: Standard errors in brackets are clustered at the closest junior high school level. 67% of pupils enrolled at a RAR public junior high school benefit from a scholarship compared to 20% of other pupils. The difference of 47 percentage points is significant at the 1% significance level. 48% of pupils whose closest public junior high school is RAR benefit from a scholarship compared to 20% of other pupils. The difference of 28 percentage points is significant at the 1% significance level.

Source: MEN-MESR DEPP, FAERE 2006 and 2007

4 Effect on individual sorting

4.1 Empirical strategy

To assess the role of the RAR program on possible sorting across schools, we analyze the effect on school choice of living in the vicinity of a RAR junior high school. Let us define the "treatment" dummy variable T_i^{NEAR}, which equals 1 if pupil i's nearest public junior high school is RAR, and 0 otherwise. Let us consider Y_i the dummy outcome variable of school choice, which represents each possible school choice that pupils face when entering 6th grade, i.e. enrolling at the nearest school, at another public school, or at a private school.

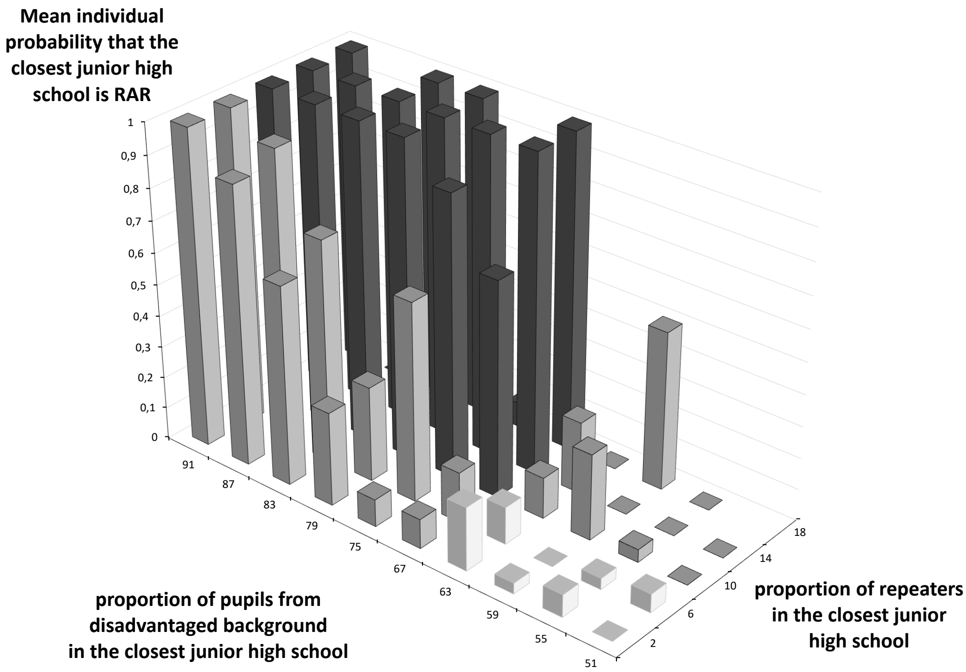
Because, as explained in the preceding part, living near a RAR school is not exogenous, a classical OLS regression of Y on T^{NEAR} is not a consistent estimator of the average treatment effect. Our identification strategy consists of using the eligibility thresholds to assess causality. More precisely, the principle of our identification strategy is the following: pupils living near a public junior high school that is above the eligibility thresholds have a higher probability that their closest (default option) school is a RAR. Some pupils would be treated exogenously, because their closest public junior high school is above the thresholds. We thus use a regression discontinuity framework.

Figure 2 highlights a clear discontinuity in the individual probability that the closest public junior high school is a RAR around the 10% threshold of repeaters in the nearest public junior high school, and around the 67% of low SES pupils in the nearest public junior high school. Under the assumption that pupils living near a junior high school just below and just above the eligibility thresholds are similar, then any discontinuity in the individual outcome around the thresholds may be interpreted as a causal effect of the proximity of a RAR school.

Let us define, for each individual i, Z_i^L the proportion of pupils who have repeated twice or more in pupil i's nearest public junior high school, and Z_i^F the proportion of low SES pupils in pupil i's nearest public junior high school. The individual probability to live near a RAR is discontinuous in (Z^L,Z^F) at the thresholds $c^L = 10\%$ and $c^F = 67\%$, respectively. Figure 3 represents the jump in the individual probability, around the two-dimensional eligibility "frontier".

Note that there are different ways to consider the regression discontinuity design here. One possibility would be to consider the two eligibility thresholds separately, and conduct separate estimations on each assignment variable. The advantage is that this may capture heterogeneous

Figure 2 – Individual probability that the nearest junior high school is RAR



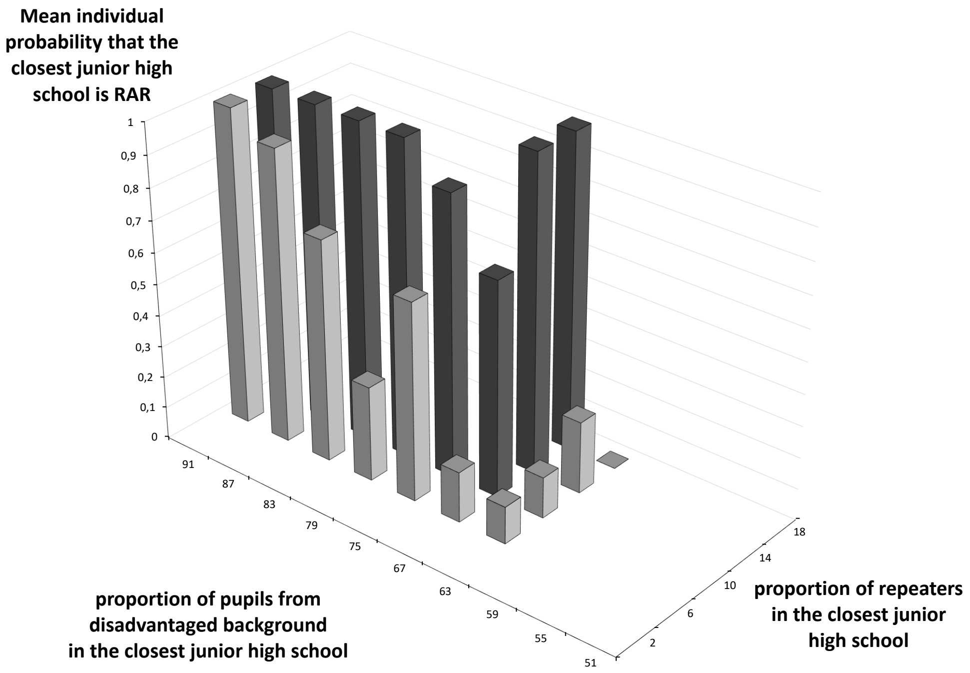
Notes: The graph presents on the x-axis, the proportion of low SES pupils in the nearest junior high school; on the z-axis, the proportion of pupils who have repeated twice or more in the nearest junior high school; and on the y-axis, the mean individual probability that the nearest junior high school is RAR (within cells of size 4 times 4).

Source: MEN-MESR DEPP, FAERE 2006 and 2007

treatment effects in the (Z^L, Z^F) dimension. The limit is that this restricts the sample to a smaller number of observations. Furthermore, the eligibility rule was specifically to be above both cutoffs, suggesting that the right specification is rather to consider the eligibility frontier. In a preceding version, we conducted a complete analysis on the two assignment variables separately (see Davezies and Garrouste, 2014, for details). Another possibility would be to only focus on the corner, i.e. consider only units below and above the eligibility frontier, but very close to the intersection of both thresholds. The limit of narrowing the analysis to this small area is the lack of power and external validity. The third possibility is to compare units above and below the eligibility frontier. This is our preferred specification, and the one that we will use in the following.

Let us then define $S_i = \min\left\{\frac{Z_i^L - 10\%}{\sigma_{Z^L}}; \frac{Z_i^F - 67\%}{\sigma_{Z^F}}\right\}$ the distance to the eligibility

Figure 3 – Individual probability that the nearest school is RAR around the eligibility frontier



Source: MEN-MESR DEPP, FAERE 2006 and 2007

frontier, with σ_{Z^L} and σ_{Z^F} the respective standard deviations[13] of Z^L and Z^F. The individual probability to live near a RAR is discontinuous in S at the cutoff $c = 0$. Assignment to treatment is not deterministic; not all units move from $T^{NEAR} = 0$ to $T^{NEAR} = 1$ above the thresholds, but the probability jumps discontinuously at the thresholds (fuzzy design).

At this stage, it is important to point out that, because we don't observe pupils' residence exact location, we may wrongly assign some pupils to a junior high school that is not the school of their catchment area, generating a misclassification problem (Horowitz and Manski, 1995).

[13]The population of compliers around $S = 0$ is a mixture of the population of compliers for $Z^L = 10\%$ with $Z^F \geq 67\%$, and the population of compliers for $Z^F = 67\%$ with $Z^L \geq 10\%$. In the definition of the parameter of interest, the respective weights of each sub-population of compliers depend on the scale factors $\frac{1}{\sigma_{Z^L}}$ and $\frac{1}{\sigma_{Z^F}}$ (Reardon and Robinson, 2012; Wong et al., 2013), unless the LATEs are the same on both parts of the frontier. Because the estimation results on each part of the frontier are qualitatively the same (see supplementary material), the choice of the scale factors is not problematic in our case. The inverse of each variable's standard deviation is used to compute a common scale for Z^L and Z^F.

It is well-known that OLS estimation in the presence of measurement error on regressors is biased. However, in our case T^{NEAR} is instrumented by S, and our RD identification strategy is robust to such error, as long as misclassification is exogenous (cf. Appendix B). Note that we are not in a situation in which a continuous measurement error affects every units and challenges identification (Davezies and Le Barbanchon, 2014; Pei, 2011; Yu, 2012).

We consistently estimate the local average treatment effect (LATE) at the frontier, by estimating the following equation by two-stage least squares (Imbens and Angrist, 1994; Hahn et al., 2001; Imbens and Lemieux, 2008), for observations such that $S \in [0-h, 0+h]$, where h is a bandwidth around the cutoff[14]:

$$Y_i = \alpha + \beta T_i^{NEAR} + \gamma' V_i + \varepsilon_i \tag{1}$$

where T_i^{NEAR} is considered endogenous and instrumented by $\mathbb{1}\{S_i \geq c\}$.

We include the additional covariates : $V_i = (\mathbb{1}\{S_i < c\}(S_i - c), \mathbb{1}\{S_i \geq c\}(S_i - c))'$ in order to allow the slope coefficient to be different on each side of the cutoff. This aims at limiting the asymptotic bias of non parametric estimators (Imbens and Lemieux, 2008).[15]

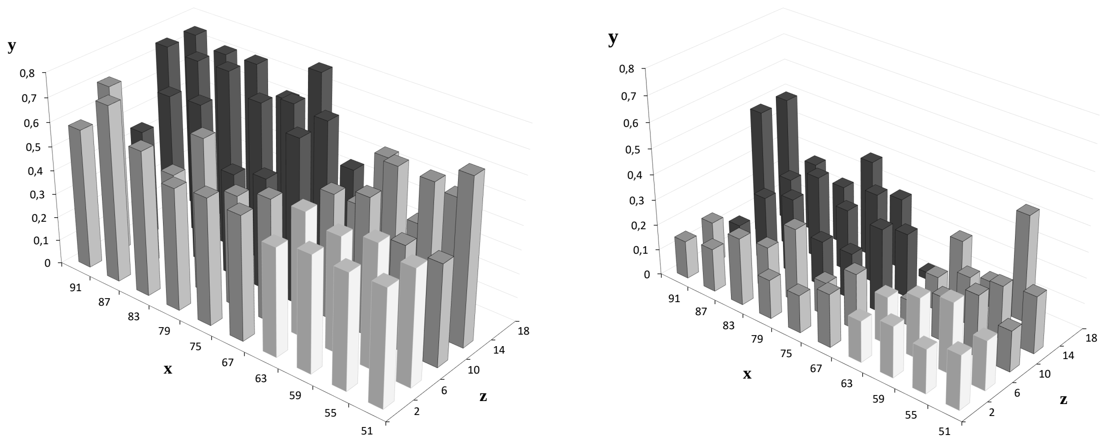
The assumption that the distribution of potential outcomes is continuous with respect to S is a necessary condition for identifying the LATE (Imbens and Lemieux, 2008). This assumption is not directly testable, but it means that pupils living near schools just above and just below the thresholds are similar. Thus, we can at least compare mean values between these two sub-populations with respect to observable characteristics in the data. For variables which are not correlated to Z, we expect mean values to be close if pupils living near schools above and below the thresholds are similar. Table 9 in Appendix D compares the sub-population of pupils whose closest school is just above the eligibility frontier with the sub-population of pupils whose closest school is just below the eligibility frontier, with respect to every individual characteristic observed in the data. According to these descriptive statistics, they do not differ much with respect to observable characteristics. Although the identifying assumption cannot be formally tested, this provides empirical support to the validity of our approach.

[14]We tested for the robustness of our estimates to the bandwidth choice. In the following, three fixed bandwidths are used. We also estimated the effects using the optimal bandwidth (Imbens and Kalyanaraman, 2012) for each outcome, using the rdbwselect command proposed by Calonico et al. (2014a,b).

[15]We also estimate the model using quadratic splines, in order to test for the robustness of our results to different specifications.

Figure 4 – Individual school choice

(a) Not enrolling at the nearest school (b) Enrolling at a private school



Notes: The graphs present on the x-axis, the proportion of low SES pupils in the nearest junior high school; on the z-axis, the proportion of pupils who have repeated twice or more in the nearest junior high school; and on the y-axis, the mean outcome probability (within cells of size 4 times 4).

Source: MEN-MESR DEPP, FAERE 2006 and 2007

4.2 Results

As an illustration of the impact of the RAR program on school choice, Figure 4 presents the mean individual probability to not enroll at the nearest school (a), and the mean individual probability to enroll at a private school (b), against the assignment variables. Although fuzzy, this graphs show an increase in the probability to not enroll at the nearest school, and in the probability to enroll at a private school, when the nearest school is above the eligibility frontier. These effects may be of large magnitude, since the mean probability to not enroll at the nearest school goes from about 50% below the frontier to about 70% above, and the mean probability to enroll at a private school jumps from about 20% below the frontier to about 40% above. This figure graphically represents the reduced form of the following estimations.[16]

Table 3 presents the results of the two-stage least square estimations around the discontinuity. The effects are estimated for different bandwidths h around the frontier, and using linear or quadratic splines.

The first stage estimates demonstrate the existence of a significant discontinuity; whatever the bandwidth, the coefficients corresponding to $\mathbb{1}\{S_i \geq 0\}$ are highly significant in the first

[16]See Table 10, and Figures 7 and 8 in Appendix F for reduced form estimations and graphs.

stage regression. In other words, living near a public junior high school where the proportion of repeaters is above the 10% threshold, and the proportion of low SES pupils is above the 67% threshold significantly increases the individual probability that the closest junior high school is a RAR, by 56 to 90 percentage points. This corresponds to the proportion of pupils whose closest junior high school is a RAR exogenously (due to the fact that their closest school is just above the thresholds) and who would otherwise not live close to a RAR. The effect of living near a RAR is then estimated on those pupils (i.e. the *compliers*) in the second stage.

The table also presents the second stage estimates for the three possible outcomes, and for different sizes of the bandwidth. For sake of clarity, we only present the coefficient corresponding to the treatment dummy T^{NEAR}, i.e. living near a RAR junior high school, in the table. These estimates are systematically negative for enrollment at the nearest school, and positive for enrollment at a private school. The results show that living near a RAR junior high school decreases the probability to attend this school by 20 to 38 percentage points, and increases the probability to attend a private school by 18 to 36 percentage points, for pupils who are treated exogenously because their closest school is just above the eligibility thresholds.

This suggests that individuals tend to avoid schools that enter the RAR program by enrolling in the private sector. Interestingly, we do not find any significant effect on the probability to enroll at another public school, suggesting that avoidance strategies are directed towards the private sector, and not the public one. This is not very surprising, since enrolling at a public school different from the catchment area one is subject to large administrative and information costs, whereas enrolling at a private school is always possible for families willing to pay the fees.

Table 3 – Estimation of the effect of living near a RAR junior high school on school choice

	RD linear spline				RD quadratic spline			
	h=0.2	h=0.3	h=0.4	h=ob	h=0.3	h=0.4	h=0.6	h=ob
Y=Enrollment in the nearest school								
				Second stage				
T^{NEAR}	-0.22*	-0.24**	-0.28**	-0.24**	-0.09	-0.20**	-0.34***	-0.38**
	(0.13)	(0.10)	(0.12)	(0.10)	(0.12)	(0.10)	(0.12)	(0.15)
				First stage				
$\mathbb{1}\{S \geq 0\}$	0.64***	0.74***	0.56***	0.77***	0.80***	0.88***	0.70***	0.67***
	(0.18)	(0.15)	(0.13)	(0.16)	(0.22)	(0.19)	(0.16)	(0.18)
Mean of Y	0.48	0.47	0.46	0.47	0.47	0.46	0.45	0.46
F-stat	13	23	18	23	13	21	21	14
Nbr obs	7,594	12,465	19,101	12,240	12,465	19,101	33,498	25,656
Nbr clusters	80	134	188	130	134	188	316	252
Y=Enrollment in another public school								
				Second stage				
T^{NEAR}	-0.03	-0.03	-0.01	-0.06	-0.05	0.02	0.14	-0.04
	(0.11)	(0.09)	(0.11)	(0.09)	(0.11)	(0.08)	(0.09)	(0.08)
				First stage				
$\mathbb{1}\{S \geq 0\}$	0.64***	0.74***	0.56***	0.78***	0.80***	0.88***	0.70***	0.90***
	(0.18)	(0.15)	(0.13)	(0.17)	(0.22)	(0.19)	(0.16)	(0.20)
Mean of Y	0.35	0.35	0.34	0.35	0.35	0.34	0.35	0.34
F-stat	13	23	18	22	13	21	21	21
Nbr obs	7,594	12,465	19,101	11,365	12,465	19,101	33,498	17,511
Nbr clusters	80	134	188	120	134	188	316	170
Y=Enrollment in a private school								
				Second stage				
T^{NEAR}	0.25**	0.27***	0.28**	0.24***	0.14	0.18**	0.20*	0.36**
	(0.12)	(0.10)	(0.13)	(0.09)	(0.10)	(0.09)	(0.11)	(0.15)
				First stage				
$\mathbb{1}\{S \geq 0\}$	0.64***	0.74***	0.56***	0.81***	0.80***	0.88***	0.70***	0.69***
	(0.18)	(0.15)	(0.13)	(0.16)	(0.22)	(0.19)	(0.16)	(0.18)
Mean of Y	0.17	0.17	0.20	0.17	0.17	0.20	0.20	0.20
F-stat	13	23	18	24	13	21	21	15
Nbr obs	7,594	12,465	19,101	11,997	12,465	19,101	33,498	26,462
Nbr clusters	80	134	188	126	134	188	316	258

Notes: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). Standard errors in brackets are clustered at the closest junior high school level. Two-stage least squares are estimated for different bandwidths of size h around each threshold."ob" denotes the optimal bandwidth (Calonico et al., 2014b). Pupils living near a RAR junior high school exogenously, due to the fact that their closest public junior high school is above the eligibility frontier, have an 18 to 36 percentage point higher probability to enroll at a private school than pupils whose closest public junior high school is not a RAR exogenously. This difference is significant.

Source: MEN-MESR DEPP, FAERE 2006 and 2007

In line with the theoretical model's predictions, these results mean that the negative signal on ex-ante school quality outperforms families' expected benefits from the RAR program. In this case, the theoretical model also predicts that families avoiding RAR schools are wealthier (larger R), and more concerned about school quality (larger θ) than families who do not avoid them. To test these predictions, we conduct a heterogeneity analysis. Because we do not observe R and θ, in the following, we use proxies of these variables based on observed social characteristics.

First, Table 4 presents the results when we allow living near a RAR school to have differentiated effects in the sample according to whether or not pupils come from a low SES background. For high SES pupils, we find that living near a RAR junior high school due to the eligibility thresholds significantly decreases the probability to attend the closest school (by 36 to 44 percentage points, depending on the bandwidth size). There is no significant effect for low SES pupils. The difference between those two sub-populations is always significant, and its magnitude is around 30 percentage points.

Living near a RAR junior high school significantly increases the probability to enroll in the private sector by 38 to 42 percentage points for the sub-population of high SES pupils, compared to an 8 to 20 percentage point increase for the sub-population of low SES pupils. This effect is significantly higher for the sub-population of high SES pupils than for low SES pupils.

Second, under the assumption that teachers have a higher preference for school quality, the effect of living in the vicinity of a RAR school should be different for children of teachers. Let us construct a dummy variable which equals one if one of the parents is a teacher, and zero otherwise. About 7% of pupils in the data have at least one parent being a teacher. Table 5 presents the effect of living in the vicinity of a treated school interacted with the teacher dummy. The results of the equality test suggest that living near a treated school decreases by about 34 to 37 percentage points more the probability to enroll at the nearest school for children of teachers than for other children. Moreover, the effect on enrollment at a private school is significantly higher for children of teachers than for other children, for every bandwidths h but the largest one.

These results thus suggest that part of parents' strategies to avoid treated schools is related to preference for school quality. The more parents are concerned about school quality, the more they avoid RAR schools.

Table 4 – Estimation of the effect of living near a RAR on school choice, according to social background

Y=Enrollment in	**the nearest school**			**another public school**			**a private school**		
				RD					
	h=0.2	h=0.3	h=0.4	h=0.2	h=0.3	h=0.4	h=0.2	h=0.3	h=0.4
Low SES (X=1) vs. High SES (X=0)									
$T^{NEAR}\times$*(X=0)*^{a}	-0.36**	-0.43***	-0.44***	-0.05	0.01	0.06	0.41**	0.42***	0.38**
	(0.15)	(0.13)	(0.15)	(0.15)	(0.11)	(0.13)	(0.20)	(0.16)	(0.19)
$T^{NEAR}\times$*(X=1)*^{b}	-0.09	-0.06	-0.13	0.01	-0.06	-0.06	0.08*	0.11**	0.20**
	(0.11)	(0.09)	(0.11)	(0.10)	(0.09)	(0.13)	(0.05)	(0.05)	(0.09)
Test $a = b$ (pvalue)	0.055	0.004	0.048	0.737	0.571	0.388	0.065	0.025	0.202
Nbr obs	7,342	12,017	18,408	7,342	12,017	18,408	7,342	12,017	18,408
Nbr clusters	80	134	188	80	134	188	80	134	188

Notes: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). Standard errors in brackets are clustered at the closest junior high school level. Two-stage least squares are estimated for different bandwidths of size h around the threshold. Low SES pupils who live near a RAR junior high school exogenously, due to the fact that their closest public junior high school is just above the eligibility frontier, have an 8 to 20 percentage point higher probability to enroll at a private junior high school than low SES pupils whose nearest junior high school is not a RAR exogenously. High SES pupils who live near a RAR junior high school exogenously, due to the fact that their closest public junior high school is just above the eligibility frontier, have a 38 to 42 percentage point higher probability to enroll at a private junior high school than high SES pupils whose nearest junior high school is not a RAR exogenously. The difference between these two estimates is significantly different from zero, except for the largest bandwidth.

Source: MEN-MESR DEPP, FAERE 2006 and 2007

To sum up, we find that the RAR program created sorting strategies. Living in the vicinity of a RAR school decreases the probability to enroll at the closest school, and the effect is driven by high SES families, and families with high preference for school quality. They enroll their children in the private sector instead. The size of the effects is large; considering that about 20% of pupils go to a private school, an 18 to 36 percentage point increase means that enrollment in the private sector more than doubles. This also means that RAR schools necessarily decrease in size, which is consistent with the literature on French compensatory education programs. Bénabou et al. (2009) show that ZEP schools size decreased in the late 1980's. Murat and Thaurel-Richard (2013) show that, in more than 25% of RAR junior high schools, school size decreases by more than 20% between 2006 and 2009. Fack and Grenet (2013) also find a massive decrease in RAR schools attractiveness, as measured by the net number of dispensation demands.

Table 5 – Estimation of the effect of living near a RAR on school choice, according to preference for school quality

Y=Enrollment in	the nearest school			another public school			a private school		
				RD					
	h=0.2	h=0.3	h=0.4	h=0.2	h=0.3	h=0.4	h=0.2	h=0.3	h=0.4
Teacher (X=1) vs. No teacher (X=0)									
$T^{NEAR}\times$*(X=0)*^{a}	-0.22*	-0.22**	-0.25**	-0.01	-0.03	-0.03	0.23*	0.25**	0.28**
	(0.13)	(0.10)	(0.11)	(0.10)	(0.08)	(0.11)	(0.12)	(0.10)	(0.13)
$T^{NEAR}\times$*(X=1)*^{b}	-0.59**	-0.56***	-0.70***	-0.29	-0.06	0.31	0.88**	0.62**	0.39*
	(0.23)	(0.18)	(0.21)	(0.35)	(0.24)	(0.24)	(0.41)	(0.25)	(0.22)
Test $a = b$ (pvalue)	0.068	0.029	0.016	0.337	0.899	0.158	0.053	0.068	0.520
Nbr obs	7,419	12,149	18,627	7,419	12,149	18,627	7,419	12,149	18,627
Nbr clusters	80	134	188	80	134	188	80	134	188

Notes: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). Standard errors in brackets are clustered at the closest junior high school level. Two-stage least squares are estimated for different bandwidths of size h around the threshold. Children of teachers who live near a RAR junior high school exogenously, due to the fact that their closest public junior high school is just above the eligibility frontier, have a 56 to 70 percentage point lower probability to enroll at the nearest junior high school than children of teachers whose nearest junior high school is not a RAR exogenously. Other pupils who live near a RAR junior high school exogenously, due to the fact that their closest public junior high school is just above the eligibility frontier, have a 22 to 25 percentage point lower probability to enroll at the nearest junior high school than non scholarship pupils whose nearest junior high school is not a RAR exogenously. The difference between these two estimates is significantly different from zero.

Source: MEN-MESR DEPP, FAERE 2006 and 2007

5 Policy implications

In terms of policy implications, our results are twofold. First, they illustrate that place-based compensatory education policies may substantially increase social segregation across schools. Second, our results challenge the way school-based policies are usually evaluated.

5.1 School-based education policies and segregation

Our analysis shows that socially more advantaged families avoid treated schools, by going to the private sector. Our findings are short-term effects, since we are only able to consider pupils entering junior high school the first two years after the beginning of the program. Because the private sector in France is not subject to the catchment area system, enrolling at a private school is the easiest way to avoid treated schools in the short-run. These effects are thus likely to depend on the local supply of private schools. Additional results show that sorting effects decrease with distance to the nearest private school.[17]

In the long-run however, one might expect high SES families to internalize school quality in

[17] Analysis with respect to the size of local private school supply is available as supplementary material.

the neighborhood, and change neighborhood to avoid treated schools (Black, 1999; Epple et al., 2001; Fack and Grenet, 2010). Although we are not able to observe potential residential effects of the program, nor to observe more recent cohorts, our results may call for future research on residential segregation.

These results also contribute to a larger debate about placed-based policies, which tries to understand how mobility and sorting of firms and individuals affect place-based policies efficiency (Lafourcade and Mayneris, 2017; Neumark and Simpson, 2015; Partridge and Rickman, 2006). For instance, Glaeser (2008) argues against place-based policies, notably because they tend to repel the rich from treated areas, and points out that externalities make it hard to anticipate their effects on welfare. In line with this literature in urban economics, our results make clear that it is very important to take individual sorting into account when studying school-based policies. Individuals do adjust to school-based education policies by changing schools, these adjustments are quick, are potentially of large magnitude, and are not random in the population, increasing social segregation across schools.

Two types of response may be considered to tackle adverse sorting effects. First, one solution could be to increase additional resources for treated schools, in order to compensate for sorting by high SES families. However, the appropriate size of additional resources, and their expected effect on families' school choices are difficult to anticipate. Second, another possibility could be to replace school-based policies with individual-based ones, in order to prevent negative signal on school quality (Maurin, 2004).

If our results highlight that adverse effects on school (and potentially residential) segregation have to be taken into account *ex-ante* in the design of school-based compensatory education policies, the following will show that families' strategic school choices also have important implications in the *ex-post* evaluation of such policies.

5.2 Effect on pupils' academic achievement

Let us now turn to the analysis of pupils' academic achievement. A naive estimation of the average treatment effect of enrollment at a RAR school on pupils' performance would be distorted by two types of bias. The first one is due to the selection of schools in the program, partly based on unobserved characteristics. The second source of bias is due to the fact that, as shown in the preceding section, pupils select themselves in (or out of) treatment, through school choice. If a difference in differences strategy (Bénabou et al., 2009) or a RDD at the school level (Beffy and Davezies, 2013) could reduce or neutralize the first bias, it does not deal with the second one.

To disentangle those different bias from the causal treatment effect, we use an empirical strategy similar to the one used in the preceding section. Let us define T_i^{RAR} the treatment variable, which equals 1 if pupil i is enrolled at a RAR junior high school in 6th grade, and 0 otherwise. Pupil i's educational achievement Y_i is measured by whether she passes the "*Brevet*" national exam at the end of junior high school.

The first column of Table 6 shows that, on average, pupils enrolled at a RAR school have an 18 percentage point significantly lower probability to pass the *Brevet* exam, and a 25 percentage point significantly lower probability to pass with honors, compared to non RAR pupils. Because RAR schools were selected on the basis of observed social and academic disadvantages, this result is not surprising.

To take these different observed characteristics into account, Columns 2 to 4 give the same naive OLS estimation on the subsample of pupils living in similar neighborhoods, i.e. pupils whose closest public junior high school is just below or just above the eligibility frontier. Even though these pupils are living close to schools with comparable observed characteristics, the pupils enrolled at a RAR school still have an 11 to 13 significantly lower probability to pass the *Brevet* than non RAR pupils. But controlling for observed characteristics is of course not sufficient.

To take into account the fact that selection of schools in the program may be due to unobserved characteristics, in Columns 5 to 7 of Table 6, we use the fuzzy regression discontinuity design. The bottom part of the table shows that pupils whose junior high school is just above the eligibility frontier have a 63 to 70 percentage point higher probability to be enrolled at a RAR school than pupils whose junior high school is just below the eligibility cutoff. The second stage estimates show that, once selection of schools in the program is taken into account, the treatment effect is still negative, but not significant anymore. However, these estimates do not take account of endogenous families' school choices.

To do that, we use the fact that pupils whose closest public junior high school is just above the eligibility cutoff have a significantly higher probability to be enrolled at a RAR school (Columns 8 to 10, bottom part of Table 6). If we assume that families cannot manipulate their location with respect to the eligibility thresholds (see next Section for a discussion of this assumption), then using this instrument allows us to take account of school choice and sorting effects. The second stage estimates of Columns 8 to 10 show that, once school choice is taken into account, the estimates are positive, though not significantly different from zero. These results suggest that the previous estimators (Columns 1 to 7) are downward-biased, and illustrate the importance of taking school choice into account to obtain reliable estimates.

To sum up, these results clearly highlight two types of bias in the evaluation of the RAR program. When both bias are taken into account, no significant impact of the program on academic achievement is detected on the sub-population of pupils treated exogenously.

Table 6 – Estimation of the effect of enrollment at a RAR on passing the *Brevet*

	OLS				RD					
					Second stage					
	Full sample	h=0.2	h=0.3	h=0.4	h=0.2	h=0.3	h=0.4	h=0.2	h=0.3	h=0.4
Y=Pass Brevet										
T^{RAR}	-0.18***	-0.13***	-0.11***	-0.11***	0.04	-0.03	-0.01	0.22	0.15	0.20
	(0.01)	(0.02)	(0.01)	(0.01)	(0.06)	(0.04)	(0.04)	(0.22)	(0.13)	(0.16)
Nbr obs	1,054,077	7,150	11,709	18,032	4,911	8,651	12,746	7,150	11,709	18,032
Nbr clusters	13,380	812	1,209	1,648	81	135	191	812	1,209	1,648
Y=Pass with honours										
T^{RAR}	-0.25***	-0.19***	-0.17***	-0.17***	-0.04	-0.06	-0.02	0.27	0.17	0.32
	(0.01)	(0.02)	(0.02)	(0.01)	(0.05)	(0.04)	(0.05)	(0.29)	(0.18)	(0.24)
Nbr obs	1,054,077	7,150	11,709	18,032	4,911	8,651	12,746	7,150	11,709	18,032
Nbr clusters	13,380	812	1,209	1,648	81	135	191	812	1,209	1,648
					First stage					
Enrolling school above cutoff					0.63***	0.70***	0.67***			
					(0.18)	(0.15)	(0.13)			
Nearest school above cutoff								0.25**	0.31***	0.25***
								(0.12)	(0.11)	(0.09)
F-stat					52	39	70	17	10	11
Nbr obs					5,342	9,373	13,716	7,594	12,465	19,101
Nbr clusters					81	135	191	845	1,255	1,711

Notes: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). Standard errors in brackets are clustered at the attended junior high school level. Two-stage least squares are estimated for different bandwidths of size h around the threshold. On average, pupils enrolled at a RAR school in 6th grade (and whose closest junior high school is near the eligibility frontier) have a 11 to 13 percentage point lower probability to pass the *Brevet* than non RAR pupils. These differences are significant at the 1% level. Pupils enrolled at a RAR school exogenously, due to the fact that their closest public junior high school is above the eligibility frontier, have a 15 to 22 percentage point higher probability to pass the *Brevet* than pupils exogenously not enrolled at a RAR. These differences are not significant.

Source: MEN-MESR DEPP, FAERE 2006 and 2007

6 Robustness tests

6.1 Placebo tests

To further test for the validity of our estimation strategy, we ran Placebo estimations, that is, we tested for the existence of discontinuities around other values than the thresholds of 10% and 67%. More precisely, we re-estimated the first stage regression around Placebo values of the forcing variable S.

Table 7 presents the results of regressing the treatment variables T^{NEAR} and T^{RAR} on $\mathbb{1}\{S \geq c\}$, for different values of c. The true cutoff is $c = 0$, and we use two Placebo cutoffs equal to $c = 0 - \sigma_S$, and $c = 0 + \sigma_S$, respectively. In other words, we test for possible discontinuities at one standard deviation below or above the true eligibility frontier. The top part of Table 7 shows that there is no significant discontinuity in the probability that the nearest junior high school is RAR around the Placebo cutoffs. Just above the true cutoff, the probability that the nearest school is RAR significantly jumps by 60 percentage points.

Similarly, the bottom part of Table 7 shows no significant discontinuity in the individual probability to be enrolled at a RAR school around the Placebo cutoffs. But the probability to be enrolled at a RAR school significantly increases by 28 percentage points above the true cutoff.

6.2 Manipulation of the forcing variables

Regression discontinuity designs rely on the assumption that the forcing variable is continuous around the threshold. In particular, it means that individuals cannot manipulate the forcing variable. In our case, remember that the selection variables are the proportion of repeaters in the nearest public junior high school and the proportion of low SES pupils in the nearest public junior high school. Both variables were measured during the school year 2004-2005.

Manipulation of these variables could be the work either of junior high schools or of families living in the catchment area. In the first case, it could be that the heads of junior high schools intentionally manipulated the information relative to the number of repeaters and the number of disadvantaged pupils in their schools to fall into the eligibility group. In the second case, families could have anticipated the program and then moved in order to live closer to a school being above (or below) the thresholds.

Both scenarios are very unlikely. The first scenario would assume that the heads of junior

Table 7 – Placebo estimations

	RD around		
	c=0 $-\ \sigma_S$	c=0	c=0 $+\ \sigma_S$
Nearest school is RAR			
$\mathbb{1}\{S \geq c\}$	-0.05	0.60***	0.07
	(0.12)	(0.11)	(0.07)
F-stat	0	29	1
Nbr obs	10,469	30,718	78,278
Nbr clusters	97	296	750
Enrollment in a RAR school			
$\mathbb{1}\{S \geq c\}$	-0.10	0.28***	0.04
	(0.11)	(0.07)	(0.04)
F-stat	1	14	1
Nbr obs	11,192	31,751	79,934
Nbr clusters	103	304	766

Notes: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). Standard errors in brackets are clustered at the junior high school level. Coefficients are estimated with the optimal bandwidth (Calonico et al., 2014b). Pupils whose closest junior high school is just above the $c = 0 - \sigma_S$ Placebo cutoff (i.e. one standard deviation below the true cutoff) have a 5 percentage point lower probability that their closest junior high school is a RAR, but this coefficient is not significantly different from zero. Pupils whose closest junior high school is just above the true cutoff have a 60 percentage point higher probability that their closest junior high school is a RAR. This coefficient is significant at the 1% level.

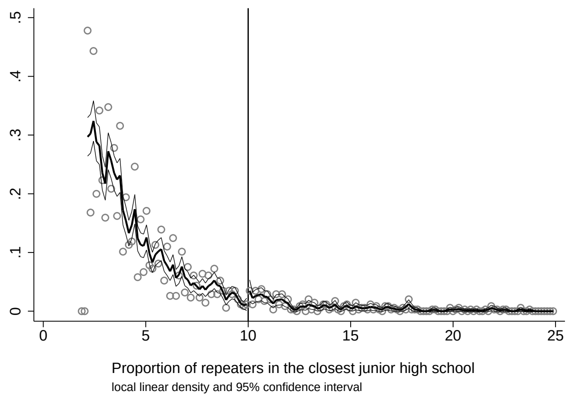
Source: MEN-MESR DEPP, FAERE 2006 and 2007

high schools were aware in 2004 of both the measures and the cutoff values that would be chosen as eligibility criteria two years later, in 2006. The second would assume that families knew whether the nearest junior high school was below or above the thresholds and would therefore have moved closer to another school. Because the eligibility criteria and the thresholds were arbitrarily selected by the French Education Ministry so as to account for 5% of pupils, and because this information was never made public, this seems very implausible. For those reasons, we do not believe that the forcing variables may have been manipulated.

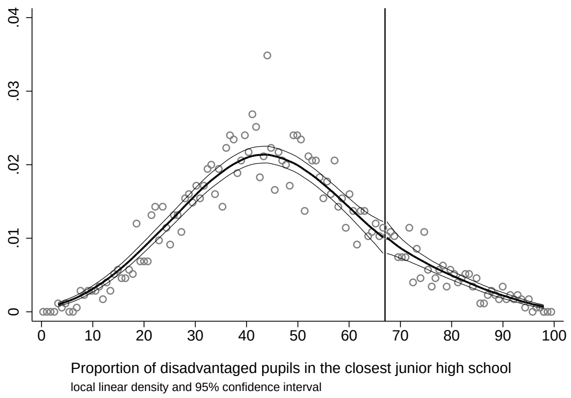
This is supported by empirical evidence. Following McCrary (2008), in case of manipulation, one would expect to find more observations above (or below) the thresholds. We thus tested for possible discontinuities in the conditional density of forcing variables. Figure 5 presents the local linear density estimates for both selection variables below and above the thresholds. Had headmasters misreported the proportion of pupils being late, or the proportion of low SES pupils in 2004 in order for their schools to enter the program, we would see many observations above the cutoff value, and few below. In the same way, had families moved closer to a school just above the thresholds to be closer to a RAR school, we would see a jump at the cutoffs. We do not see, however, any significant discontinuity around the thresholds.

Figure 5 – McCrary Density Test

(a) Forcing variable Z^L



(b) Forcing variable Z^F



Source : MEN-MESR DEPP, FAERE

7 Conclusion

The objective of this paper is to identify the effect of place-based compensatory education on individual sorting across schools. To reach this goal, we have estimated the causal impact of the French compensatory education RAR program on school choice. Using an original geocoded data-base and a reliable identification strategy, we find that the program decreases the individual probability to attend the closest public school, and symmetrically increases the probability to attend a private school, by 20 to 38 percentage points for pupils living near a treated school exogenously, due to the eligibility scheme. This means that the proportion of pupils enrolling in the private sector in 6th grade more than doubles. We find that the effects are heterogeneous with respect to social characteristics; they are completely driven by high SES pupils. Interestingly, sorting effects also seem to be larger for the families having a higher valuation of school quality. These results thus suggest that the RAR status is interpreted as a negative signal on school quality by socially advantaged families. Our results then show that selection and sorting bias completely explain the program's negative effects on pupils' educational outcomes; once these bias are taken into account, we don't find any significant effect of the program on pupils' academic achievement as measured by the "*Brevet*" national exam scores.

Our findings are true locally, for pupils who live near a school that is close to the thresholds. The findings cannot be generalised to the overall population. But they show that endogenous sorting effects do exist, and they are not negligible. Since we are comparing pupils living near schools just below and just above the eligibility thresholds, we compare *a priori* pupils in the vicinity of schools at the margin of eligibility. According to the eligibility criteria, the schools we consider are the less disadvantaged ones. Extrapolating our results to schools farther from the eligibility frontier is not straightforward; one would need to investigate how families respond to the RAR signal for more (or less) disadvantaged schools.

These results may shed new light on how to evaluate place-based education policies. Not only are treated individuals different *ex ante* with respect to the general population (selection bias), but they may also select themselves into (or out of) treated schools or treated zones, resulting in a sorting bias. These findings may thus help explain some results of the literature; sorting effects may be a reason why empirical studies fail to find positive effects, or even find negative effects of compensatory education in secondary education. If the most socially advantaged pupils are more likely to avoid treated schools, then usual estimators are downward-biased. This provides material for future research. First, one needs to control for individual sorting when evaluating place-based policies. Second, one needs to examine the existence of dynamic peer effects, due to the fact that potentially good peers avoid treated schools.

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Appendix

A Theoretical Predictions

The following Proposition details how families' school choices depend on their beliefs, income R, and preference for school quality θ, in the theoretical model detailed in Section 2.

Proposition A.1 (Beliefs and sorting on (R,θ)**)**
Assume that u is strictly concave and such that $\lim_{c\downarrow 0} u(c) = -\infty$ and $\lim_{c\uparrow 0} u'(c) = 0$. There are two equilibria depending on families' beliefs about school quality.

1. *If $\Delta\mathbb{E}(v) \leq \bar{\delta}$, school A enrolls more families when it is RAR than when it is non-RAR. Moreover :*

   (a) *For a given θ, there exist two thresholds of income $\underline{R}^{opt} \leq \overline{R}^{opt} \leq +\infty$, such that:*

   - *Families with income lower than $\underline{R}^{opt}$ always choose school A,*
   - *Families with income between $\underline{R}^{opt}$ and $\overline{R}^{opt}$ choose school A if and only if school A is RAR,*
   - *Families with income larger than $\overline{R}^{opt}$ always choose private school B.*

   (b) *For a given income R, there exist two thresholds $\underline{\theta}^{opt} \leq \overline{\theta}^{opt} \leq +\infty$, such that :*

   - *Families with θ lower than $\underline{\theta}^{opt}$ always choose school A,*
   - *Families with θ between $\underline{\theta}^{opt}$ and $\overline{\theta}^{opt}$ choose school A if and only if school A is RAR,*
   - *Families with θ larger than $\overline{\theta}^{opt}$ always choose private school B.*

2. *If $\Delta\mathbb{E}(v) \geq \bar{\delta}$, school A enrolls less families when it is RAR than when it is non-RAR. Moreover :*

   (a) *For a given θ, there exist two thresholds of income $\underline{R}^{opt} \leq \overline{R}^{opt} \leq +\infty$, such that :*

   - *Families with income lower than $\underline{R}^{opt}$ always choose school A,*
   - *Families with income between $\underline{R}^{opt}$ and $\overline{R}^{opt}$ choose school A if and only if school A is not RAR,*
   - *Families with income larger than $\overline{R}^{opt}$ always choose private school B.*

   (b) *For a given income R, there exist two thresholds $\underline{\theta}^{opt} \leq \overline{\theta}^{opt} \leq +\infty$, such that :*

   - *Families with θ lower than $\underline{\theta}^{opt}$ always choose school A,*
   - *Families with θ between $\underline{\theta}^{opt}$ and $\overline{\theta}^{opt}$ choose school A if and only if school A is not RAR,*
   - *Families with θ larger than $\overline{\theta}^{opt}$ always choose private school B.*

Proof: Families prefer school A to school B if and only if:

$$\frac{u(R)-u(R-p_B)}{\theta} > \mathbb{E}_{\pi'}(v(q_B)) - \mathbb{E}_{\pi_0}(v(q_A)) + \Delta\mathbb{E}(v) - \overline{\delta} \qquad \text{when } A \text{ is treated,}$$
$$\frac{u(R)-u(R-p_B)}{\theta} > \mathbb{E}_{\pi'}(v(q_B)) - \mathbb{E}_{\pi_0}(v(q_A)) \qquad \text{when } A \text{ is not treated}$$

For a given θ, the function $R \in [p_B; +\infty[\mapsto \frac{u(R)-u(R-p_B)}{\theta}$ is strictly decreasing from $+\infty$ to 0. If $\mathbb{E}_{\pi'}(v(q_B)) - \mathbb{E}_{\pi_0}(v(q_A)) + \Delta\mathbb{E}(v) - \overline{\delta} \leq 0$, then let us fix $R_T = +\infty$. Otherwise, there exists a unique R_T such that:

$$\frac{u(R_T)-u(R_T-p_B)}{\theta} = \mathbb{E}_{\pi'}(v(q_B)) - \mathbb{E}_{\pi_0}(v(q_A)) + \Delta\mathbb{E}(v) - \overline{\delta}$$

Similarly, if $\mathbb{E}_{\pi'}(v(q_B)) - \mathbb{E}_{\pi_0}(v(q_A)) \leq 0$, let us fix $R_{NT} = +\infty$. Otherwise, there exists a unique R_{NT} such that:

$$\frac{u(R_{NT})-u(R_{NT}-p_B)}{\theta} = \mathbb{E}_{\pi'}(v(q_B)) - \mathbb{E}_{\pi_0}(v(q_A))$$

If $\Delta\mathbb{E}(v) \leq \overline{\delta}$, we have that $R_{NT} \leq R_T$, and then denoting $\underline{R}^{opt} = R_T$ and $\overline{R}^{opt} = R_{NT}$, we conclude that 1.(a) holds.
Similarly, if $\Delta\mathbb{E}(v) \geq \overline{\delta}$, we have that $R_T \geq R_{NT}$, and denoting $\underline{R}^{opt} = R_{NT}$ and $\overline{R}^{opt} = R_T$, we conclude that 2.(a) holds.

Because, for a given R, the function $\theta \mapsto \frac{u(R)-u(R-p_B)}{\theta}$ is strictly decreasing, a similar reasoning can be used to prove 2.(a) and 2.(b).

B Robustness to the error on the catchment area school

Our identification strategy relies on the use of the closest school (defined as the closest school to pupil's primary school) as a proxy for the catchment area school. Let D denote the dummy variable, which is equal to 1 if the catchment area school is the same as the "closest" school, and 0 otherwise. Let $T^*, Y(0)^*, Y(1)^*, Y^*$ and S^* respectively denote the treatment variable, potential outcomes, actual outcome, and running variable for the school of the catchment area. As soon as $D = 1$, we have that $T^* = T^{NEAR}$, $Y(0)^* = Y(0)$, $Y(1)^* = Y(1)$, $Y^* = Y$, and $S^* = S$. When $D = 0$, there is a misclassification problem. Let us assume the following:

Assumption B.1 (Ignorable Misclassification)

1. *No almost-sure error: for any value of s in a neighborhood of 0,*

$$\mathbb{P}(D = 1|S = s) > 0,$$

$$\mathbb{P}(D = 1|S^* = s) > 0.$$

2. *Exogenous misclassification: for any value of s in a neighborhood of 0,*

$$T, Y(0), Y(1) \perp\!\!\!\perp D|S = s,$$

$$T^*, Y(0)^*, Y(1)^* \perp\!\!\!\perp D|S^* = s.$$

The first assumption ensures that, with positive probability, the closest school corresponds to the school of the catchment area. The second one states that the probability of misclassification is not correlated with treatment and potential outcomes (conditional on the running variable).

Proposition B.2 (Robustness) *If Assumption B.1 holds with the usual assumption of the fuzzy RD design for $T^*, Y(0)^*, Y(1)^*, S^*$ (Hahn et al., 2001), then both the identification and estimation of the LATE are robust to the fact that variables Y, T^{NEAR} and S are used instead of Y^*, T^* and S^*.*

Proof : For any value s in a neighborhood of the frontier, Assumption B.1 ensures that:

$$\mathbb{E}(Y^*|S^* = s) = \mathbb{E}(Y^*|S^* = s, D = 1),$$

and

$$\mathbb{E}(Y|S = s) = \mathbb{E}(Y|S = s, D = 1).$$

By definition of D, we have $Y = Y^*$ and $S = S^*$ if $D = 1$, then:

$$\mathbb{E}(Y^*|S^* = s) = \mathbb{E}(Y|S = s).$$

A similar reasoning ensures that $\mathbb{E}(T^*|S^* = s) = \mathbb{E}(T^{NEAR}|S = s)$. Because the usual assumption of fuzzy RD design holds for T^*, Y^*, S^*, we know that $\lim_{c\downarrow 0} \frac{\mathbb{E}(Y^*|S^* \in [0;c]) - \mathbb{E}(Y^*|S^* \in [-c;0])}{\mathbb{E}(T^*|S^* \in [0;c]) - \mathbb{E}(T^*|S^* \in [-c;0])}$ converges to the LATE. So this is also the case for $\lim_{c\downarrow 0} \frac{\mathbb{E}(Y|S \in [0;c]) - \mathbb{E}(Y|S \in [-c;0])}{\mathbb{E}(T^{NEAR}|S \in [0;c]) - \mathbb{E}(T^{NEAR}|S \in [-c;0])}$.

C Characteristics of pupils' municipality

Table 8 – Characteristics of pupils' municipality of residence in the sample

Characteristics of municipality of	pupils not living near a RAR	pupils living near a RAR	Test (p-value)
Median households revenue	28,536	24,024	<0.001
	(132.8)	(376.4)	
Unemployment rate	7.63	8.67	<0.001
	(0.031)	(0.196)	
Population density	1,546	3,509	<0.001
	(81.7)	(307.7)	
Nbr obs	967,563	39,238	

Notes: Standard errors in brackets are clustered at the municipality (of residence) level. Pupils living in the vicinity of a RAR public junior high school live in municipalities where the median households revenue is 28,536 euros, on average, compared to 24,024 for other pupils. The difference of 4,512 euros is significant at the 1% significance level.

Source: MEN-MESR DEPP, FAERE 2006 and 2007

D Mean comparison of subsamples above and below the cutoff

Table 9 – Individual characteristics around the discontinuity

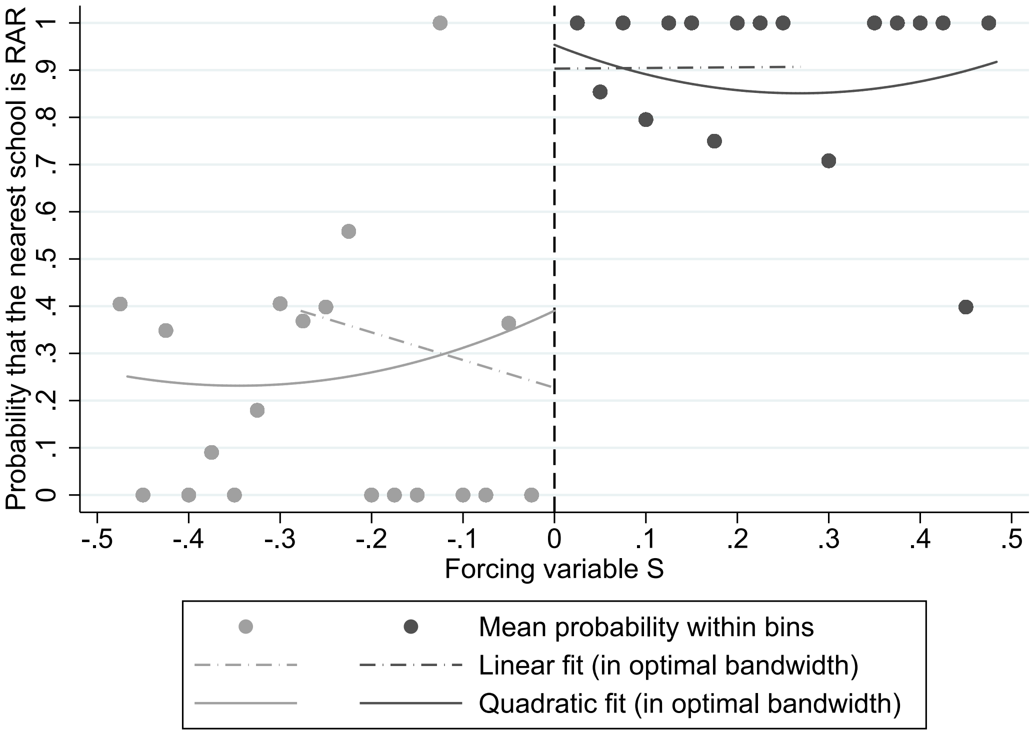
	Mean comparison of:						
	Pupils living near a RAR vs. not				Pupils above vs. below disc		
	Total	h=0.2	h=0.3	h=0.4	h=0.2	h=0.3	h=0.4
Male	-0.00	0.00	0.01	0.01	0.00	0.02*	0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age at 6th grade	0.01***	0.01	0.01	0.02	0.01	0.01	0.00
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Born French	-0.06***	-0.00	-0.07	-0.09*	0.10	0.03	-0.04
	(0.01)	(0.07)	(0.06)	(0.05)	(0.08)	(0.06)	(0.05)
Low SES	0.02***	-0.01	-0.02	-0.01	-0.00	-0.01	-0.00
	(0.00)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Scholarship	0.06***	0.11***	0.11***	0.12***	0.05	0.06*	0.05
	(0.00)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
Test (pvalue)	0.000	0.058	0.001	0.000	0.680	0.139	0.482
Nbr obs	1,071,395	7,342	12,017	18,408	7,342	12,017	18,408
Nbr clusters	9,931	80	134	188	80	134	188

Notes: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). Standard errors in brackets are clustered at the closest junior high school level. Mean differences are estimated for different bandwidth of size h around the cutoff. The p-value corresponds to the joint significance test. Pupils who benefit from a scholarship have a higher probability to live in the vicinity of a RAR junior high school (6 percentage points more) than non scholarship pupils, all other characteristics being equal. This difference is significant at the 1% level and remains significant for different sub-samples of observations lying just around the cutoff.

Source: MEN-MESR DEPP, FAERE 2006 and 2007

E Graph of discontinuity around the eligibility frontier

Figure 6 – Individual probability that the nearest school is RAR, around the eligibility frontier



Source: MEN-MESR DEPP, FAERE 2006 and 2007

F Reduced form estimations

Table 10 – Reduced form estimation of the effect of being above the eligibility threshold

	Reduced form linear spline				Reduced form quadratic spline			
	h=0.2	h=0.3	h=0.4	h=ob	h=0.3	h=0.4	h=0.6	h=ob
Y=Enrollment in the nearest school								
$\mathbb{1}\{S \geq 0\}$	-0.14*	-0.18**	-0.16**	-0.18**	-0.07	-0.18*	-0.24***	-0.25***
	(0.08)	(0.08)	(0.06)	(0.08)	(0.10)	(0.09)	(0.08)	(0.09)
Mean of Y	0.48	0.47	0.46	0.47	0.47	0.46	0.45	0.46
Nbr obs	7,594	12,465	19,101	12,240	12,465	19,101	33,498	25,656
Nbr clusters	80	134	188	130	134	188	316	252
Y=Enrollment in another public school								
$\mathbb{1}\{S \geq 0\}$	-0.02	-0.02	-0.00	-0.05	-0.04	0.02	0.10	-0.04
	(0.07)	(0.06)	(0.06)	(0.06)	(0.08)	(0.07)	(0.07)	(0.07)
Mean of Y	0.35	0.35	0.34	0.35	0.35	0.34	0.35	0.34
Nbr obs	7,594	12,465	19,101	11,365	12,465	19,101	33,498	17,511
Nbr clusters	80	134	188	120	134	188	316	170
Y=Enrollment in a private school								
$\mathbb{1}\{S \geq 0\}$	0.16***	0.20***	0.16***	0.19***	0.11*	0.16**	0.14**	0.25***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.08)
Mean of Y	0.17	0.17	0.20	0.17	0.17	0.20	0.20	0.20
Nbr obs	7,594	12,465	19,101	11,997	12,465	19,101	33,498	26,462
Nbr clusters	80	134	188	126	134	188	316	258

Notes: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). Standard errors in brackets are clustered at the closest junior high school level. Pupils whose closest junior high school is just above the eligibility frontier have a 14 to 25 percentage point significantly lower probability to enroll at their closest junior high school.

Source: MEN-MESR DEPP, FAERE 2006 and 2007

Figure 7 – Individual probability to enroll at the nearest school, around the eligibility frontier

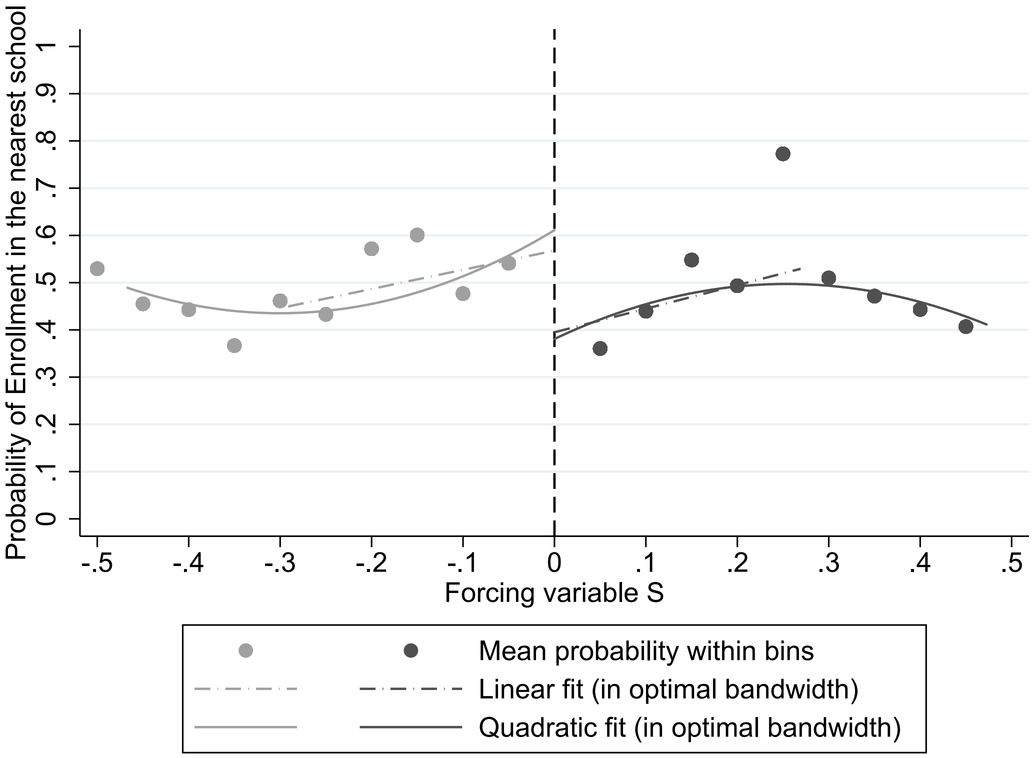
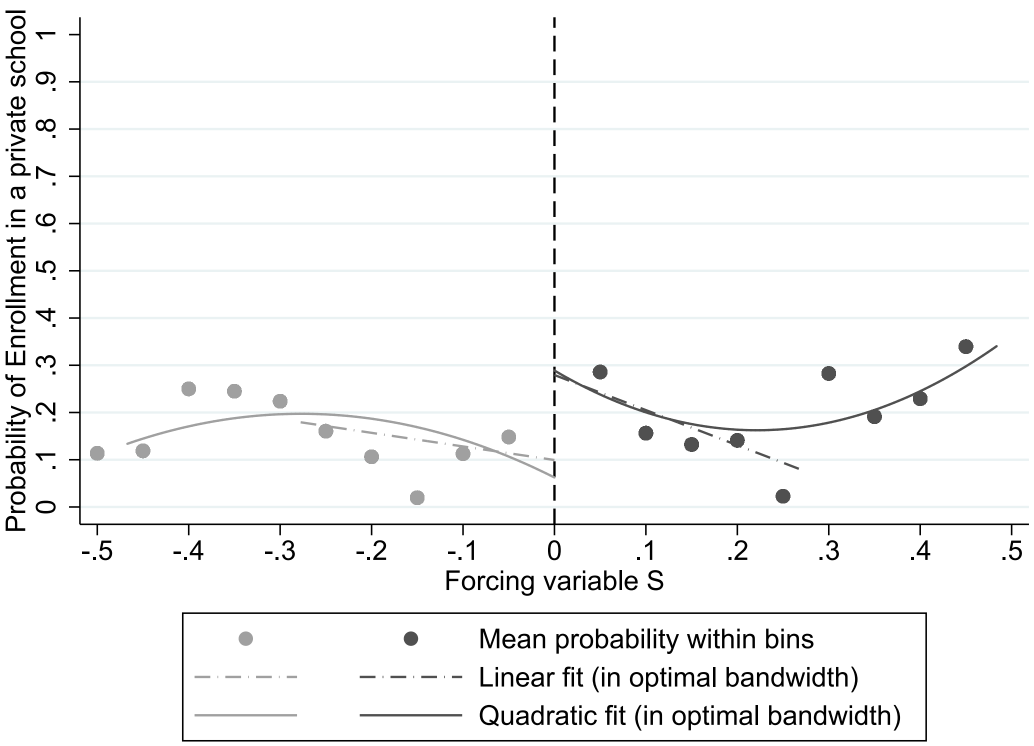


Figure 8 – Individual probability to enroll at a private school, around the eligibility frontier



Source: MEN-MESR DEPP, FAERE 2006 and 2007