Does a Part-Time School Principal Harm Students? Italian School Consolidation Process and Student Outcomes*

Sara Pau[1] and Adriana Di Liberto[1,2]

[1] *University of Cagliari*

[2] *IZA and CRENoS*

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Abstract

Schools are the main producers of human capital, which plays a key role in the process of economic growth. In this paper we aim to assess the impact of the Italian secondary schools consolidation process on student outcomes. We exploit the fuzzy discontinuity in treatment regime and apply a continuity-based local polynomial approximation Fuzzy RDD. Estimation results show that the program exposure has had detrimental heterogeneous effects in upper secondary schools, especially for treated schools far away from the directional school, where the school principal is based. As a result, the isolation of the merged schools appears as a causality channel that makes the principals' responsibilities substantially aggravated. We conclude that the school consolidation process appears as a cost-saving policy that may fail to consider the indirect costs arising in term of poorer school performance, which may subsequently produce labor market inequalities due to losses in human capital accumulation.

Keywords: School Consolidation; Student dropouts; Schooling Outcomes; Management quality

*Contacts: Sara Pau, sarapau@unica.it, Dipartimento di Scienze Economiche e Aziendali, University of Cagliari, via S. Ignazio 17, 09123, Cagliari, ITALY.

1 Introduction

Human capital plays a crucial role in the process of economic growth (Lucas 1988, Barro 2001, Romer 1990), which has been shown to be closely related to the quality of schooling (Hanushek and Kimko, 2000). The underlying mechanism sees economies with more human capital innovating at a higher rate than those with less human capital, implying that societies with larger human capital in their workforce register more productivity gains and, as a result, a path of continued economic growth.

Since schools are the main "producers" of human capital, understanding the factors linked to variations in school performance becomes a key point to forward-thinking policy makers interested to trace economic development far into the future. In fact, many countries around the world seek to improve their schools aiming to enhance the skills and employability of their youth or to reduce inequalities in economic outcomes within their population (Hanushek and Woessmann, 2010).

Since 1990s, Italian institutional settings have changed and policies mostly oriented at containing costs have been the new rage. The school consolidation process (*Dimensionamento Scolastico*) belongs to this framework (Fontana, 2008). Indeed, new centralized criteria for the optimal schools size (both primary and secondary schools) have been introduced with the D.P.R. 233/1998, aiming at ensuring the optimal use of professional and instrumental resources. More specifically, to acquire or maintain legal personality, educational institutions must normally have a population between 500 and 900 students. Some exceptions are provided. In small islands, mountain municipalities, as well as in geographic areas characterized by ethnic or linguistic specificity, the school population can be reduced to 300 pupils. If schools do not reach the above mentioned thresholds, horizontal unification is planned, with other schools of the same grade included in the same territorial area, or vertical in comprehensive schools, according to the educational needs of the local area. Moreover, in some specific situations, a school where the position of the School Principal (SP hereafter) is left vacant, the Regional School Office can appoint a regent. What, in any case, the two schemes - unification and regency - have in common is the absence of a SP who is constantly based in the school. For this reason we adopted in this analysis the definition of "Part-Time School Principal", namely a SP that is in charge to guarantee simultaneously the functioning of more schools: the "directional school" where he or she was already based, plus one or more merged complexes. Hence, from a single merged school point of view, this policy design results in having a SP "borrowed" from the directional school that has to share his working time and effort among more than one schools.

During the school year 2010/2011, 57.6% of total Italian schools were involved in the consolidation process, having then a shared SP.

The administrative cost reduction arising from the consolidation appear as a trivial result, meeting at least one of the policy change objectives related to ensure the optimal use of instrumental resources. What is neither trivial in this picture nor already assessed in the existing literature, is a clear understanding whether the use of professional resources is also optimal. More specifically, is the centralization of school management a win-win policy?

Since there is a growing attention regarding the role played by the SP in running the school (Bloom *et al.*, 2015), which is increasingly considered crucial, this study is aimed at investigating the impact of school consolidation process on student dropout behaviour.

In fact, Hanushek *et al.* (2008) investigated the underlying causes of dropping out of school and found that a student is much less likely to remain in school if attending a low quality school rather than a high quality school. Yet, mass-media and involved actor groups have voiced concerns that these mergers substantially aggravate the SP responsibilities and may have negative implications for the school performance, resulting in poorer student outcomes and, ultimately, less economic growth.

Due to the availability of data, we focus on Lower Secondary Schools (LSS henceforth) and Upper Secondary Schools (USS in what follows) during the school year 2010/2011. The student outcomes of interest are two different measures of dropout behaviour. They include voluntary dropouts, namely students that spontaneously stop attending classes during the year, and grade retention, measured by those students that are not admitted to the next class. They represent the "two sides of the same coin" since both of them hinder the expected school completion levels and give reason to concern about.

The analysis is performed both at school and cohort level.

The paper is structured as follows. Section 2 provides details on the consolidation policy. Section 3 reviews the literature framework to which this analysis belongs. In section 4 we discuss the data. In section 5 the methodology. Section 6 presents the results and some robustness checks, section 7 concludes.

2 Institutional Settings

During the school year 2010/2011, the optimal size of educational institutions was governed by the D.P.R. 233/1998. Article 2 states: "The administrative, organizational, didactic and educational research and planning autonomy is recognized to the educational institutions of every order, including those already endowed with juridical personality, that reach dimensions suitable to guarantee the optimal balance between the demand and the organization of the education supply."

Further, the parameters are specified: "[...] To acquire or maintain legal personality, educational institutions must normally have a population, consolidated and predictably stable for at least five years, between 500 and 900 students; these indexes are taken as terms of reference to ensure the optimal use of professional and instrumental resources." Some exceptions are also provided. In small islands, mountain municipalities, as well as in geographic areas characterized by ethnic or linguistic specificities, the reference "[...] indexes can be reduced to 300 pupils for institutions including pre-school, primary and secondary schools, or upper secondary education which include courses or sections of different order or type [...]; in the above mentioned locations that are in conditions of particular isolation can also be constituted institutions inclusive of schools of every order and degree. The maximum index - 900 pupils - can be exceeded in areas of high population density, with particular regard to secondary educational institutions for training purposes that require structural assets, laboratories and workshops of high artistic or technological value." Moreover, in order to preserve the peculiarity of some North-Est local areas, schools with Slovenian teaching language will maintain the autonomy even in the absence of the minimum parameters of 300 pupils.

If schools do not reach the aforementioned reference indexes, horizontal unification is planned, with schools of the same grade included in the same territorial area, or vertical in comprehensive schools, according to the educational needs of the territory and local area planning.

To ensure the permanence in the territorial areas of schools that do not reach, alone or combined with schools of the same grade, optimal dimensions, educational institutions including kindergarten, primary and secondary schools are constituted, assuming the name of *Istituti Omnicomprensivi*. With the same purpose and to ensure the necessary variety of educational programs proposed by each institute and to meet the demand for education expressed by the school population, the unification of institutions of different order or type that do not reach, separately, the optimal dimensions is practicable. These institutions assume the name of *Istituti di Istruzione Superiore*.

The educational institutions merger plans are defined in provincial conferences for the organization of the school network, in compliance with the planning guidelines and general criteria previously adopted by the regions. The regions approve the regional merger plan, based on the provincial plans, by December 31 of the school year preceding the one to which the plan refers.

2.1 Regencies and Unifications

In some specific situations, a school where the position of the SP is left vacant, the Regional School Office can appoint a regent, that is a SP of another educational institution who is in charge to guarantee simultaneously the functioning of two or more schools.

The SP position may be vacant for several reasons:

- prolonged illness, leave or acceptance of other positions by the previous SP.
- Merger: if the number of students does not reach the thresholds set by the D.P.R. 233/98 and it is not possible to proceed to unification with other plexuses (e.g. because the total number of students after the unification would exceed the maximum threshold).[1]
- Retirement of the previous SP without the appointment of the new SP, regardless the number of students enrolled in the school.

The regency of the SP differs from the horizontal and vertical unifications for various reasons and concern the collaborators of the SP and the administrative apparatus. The regent SP may have a vicar both in the school where he is effective and in the school where he is a regent, the SP of an unified school has only one vicar.

A SP can however appoint collaborators up to 10% of the teaching staff, and often, in the unified plexuses,

[1] Only in this case, the Director of General and Administrative Services (DGAS) will be a regent as well.

there is the figure of the "Director of Plexus".

The schools under regent maintain their own administrative apparatus, the unified schools do not but, as already specified, only in case of regency for merger, the DGAS will also be a regent "borrowed" from another school. In all other cases of regency, the school will have its own secretarial offices.

Conversely, in the case of unification, a single administrative apparatus is envisaged with competence both on directional school and on unified plexuses. What, in any case, the two schemes - unification and regency - have in common is the absence of a SP who is constantly based in the directional school. For this reason we adopted in this analysis the definition of "part-time School Principal".

3 Literature Review

Our analysis contributes to two strands on the existing literature, one linked to the role of SP on school performance and pupils' outcomes and one related to the debate regarding the centralized versus decentralized provision of public services.

A large number of studies link high-quality leadership with positive school outcomes, such as student achievement (see Hallinger and Heck, 1998).

SPs may affect pupils outcomes through a variety of channels. In the Italian context, as school leaders, they are in charge to set up the school-level policy decisions. Although they have little influence on the composition of the school workforce, they still maintain considerable power on teacher supervision and retention, student discipline and student allocation to teachers and classes. They can also potentially have an impact on introducing new curricula and teaching techniques (Coelli and Green, 2012) and are responsible for monitoring the quality of instruction delivered by teachers (Clark *et al.*, 2009).

Moreover, since teachers quality matters to student achievements, as pointed out by a voluminous literature (see, among others, Rivkin *et al.* 2005, Aaronson *et al.*2007, Konstantanopoulos 2007, Kane *et al.* 2008, Koedel 2008 and Leigh 2010), the role of SP becomes crucial as long as he or she can have an impact on teachers composition and performance.

Further, Grissom (2011) finds that SP effectiveness is associated with greater teacher satisfaction and a lower probability that the teacher leaves the school within a year. The impact of principal skills on retaining teachers is significant since high rates of teacher turnover negatively impact school performance through several channels: high turnover means greater school instability, disruption of curricular cohesiveness and a continual need to hire inexperienced teachers, who typically are less effective, as replacements for teachers who leave. Moreover, the positive impacts of principal effectiveness on teacher satisfaction and lower turnover is even greater in disadvantaged schools. These findings support those policies focused on getting the best principals into the most challenging school environments.

Bloom *et al.* (2015) answer the question whether the managerial practices are related to meaningful educational outcomes by means of a cross-sectional analysis and survey methodology over 1,800 schools randomly sampled across eight countries. They constructed a management quality index starting from information on management practices adoption collected by double-blind telephone interviews with school principals. More in details, the survey investigated the adoption of 20 basic management practices, where the level of adoption was evaluated through a scoring grid that ranged from one, indicating a "worst practice", to five, signaling a "best practice".The index was then a result of an average across those 20 management practice measures in four areas of management: operations, monitoring, target setting and people. They find that one standard deviation increase in the abovementioned managerial index is associated with a 0.232 to 0.425 standard deviation increase in students' outcomes, namely educational achievements involving standardize and non-standardize examination results.

Moreover, higher principal turnover is also found to occur in low achieving schools and the switching SP are more likely to move to higher performing schools (Cullen and Mazzeo, 2008, Branch *et al.*, 2012 and Miller, 2009).

Further, Clark *et al.* (2009), present evidence on the relationship between principal characteristics and school performance using data from New York City Department of Education. They find that schools perform better when they are led by experienced principals, particularly for math test scores and student absences. Thus they confirm the well known learning by doing principle: workers performing more tasks will become more productive with experience at the task, especially when the task is as demanding as running a school. They also warn about the high potential cost in term of policy implications of having experienced principals leave their jobs, and provide evidence on the benefits associated with retaining experienced principals. As a result, their findings alert district administrators to the distributional consequences arising from higher rates of principal turnover in disadvantaged schools.

Grissom and Loeb (2011) try to add a step forward on the literature that recognizes that SPs affect school outcomes, by shedding light on how principals influence these outcomes, namely the specific skills that principals need to achieve school success. They use principals' self-assessments on 42 tasks to distinguish five effectiveness dimensions (Instruction Management, Internal Relations, Organization Management, Administration, and External Relations).[2] In their findings, only the principals' Organization Management skills, consistently predicts students' math and reading achievement gains.[3]

Further, Coelli and Green (2012), using the method that Rivkin *et al.* (2005) used to analyze teacher impacts, estimated the effect of individual SPs on student high school graduation probabilities and grades from the Canadian province of British Columbia. More specifically, they are able to isolate the effect of principals from the effect of schools thanks to the SP rotation across schools occurred by districts. They find that a principal who is one standard deviation better in the principal effects distribution is associated with higher graduation rates by 2.6 percentage points. The authors also hypothesize that the effect of principals may not be immediately evident but it may take numerous years for them to exert a significant impact on student outcomes. In particular, in a school where the principal turns over every year, he or she may not be able to have a full sizable effect on the school, finding that English exam scores will be higher by 2.5 percentage points if principals are given time to fully " leave their mark" on the school.

Being a school principal is a stressful job, and many school districts find difficult to attract quality applicants and to keep successful principals in their jobs. Coelli and Green results confirm that public policies should make an effort to retain good school principals.

Furthermore, the longstanding problem in public finance regarding the trade-off between centralized and decentralized provision of public services has been of interest to public economists (see e.g., Boffa *et al.* 2015, Besley and Coate 2003), and it has been applied to the educational field as well (Galiani *et al.*, 2008). The standard approach, formalized by Oates (1972), assumes that the main drawback

[2] Instruction Management is related to the set of tasks principals conduct to support and improve the implementation of curricular programs. Internal Relations is linked to the capability of principals to building strong interpersonal relationships within the school. Organization Management refers to the set of tasks principals exert to oversee the functioning of the school and to pursue the school's medium and long-term goals. Administration regards more routine administrative duties and tasks executed to comply with state or federal regulations. External Relations addresses the capability to work with stakeholders outside the school.

[3] Math and reading scores from the Florida Comprehensive Assessment Test (FCAT) during the years 2007 and 2008 at the student-level.

with a centralized system is that it produces a "one size fits all" provision of public goods and services which does not reflect, and eventually satisfy, local needs. While centralization can exploit economies of scale and scope better, and profit from policy coordination - which becomes very important in presence of spillovers - local bureaucrats are believed to have more information on the local specific needs than the upper-tier governments and many of the public goods and services needed by citizens are often community- and site-specific. This argument can be easily translated into educational environment where, on one hand, the needs of students may be school-specific and educational strategies require to be tailored accordingly; on the other hand, an upper-tier school management can have economies of scale in designing curricula and in prescribing and enforcing minimum quality standards (Bardhan, 2002).

4 Data

We focus on Italian Secondary Schools, both lower and higher order. We link multiple sources of administrative micro-data at the school level mainly issued by the Ministry of Education and available for the school year 2010/2011, through the project "Scuola in Chiaro". Our dependent variables are proxies for student failure and include student dropouts, namely students that voluntarily stop attending classes during the year, and students that are not admitted to the next class.[4] The analysis is made at school level with regard to both dependent variables. Additionally, student dropouts data are available at cohort level as well, and we therefore conduct the analysis with this greater level of disaggregation only for dropouts. We also allow for heterogeneous effects by distinguishing between the geographical characteristics of the schools, driving distance from the directional school (where the SP is based), and USS typology. The available data on the Register of Italian Schools contain the unique national identification code (*Codice Meccanografico*) and the address for all school complexes with also the indication of their directional school address. By comparing the addressed of the plexus and the directional school, we are able to identify treated (different address, SP not in place) to controls (directional schools, SP in

[4]Eurostat uses the definition of "early school leavers" to indicate "[...]the population aged 18 to 24 having attained at most lower secondary education and not being involved in further education or training". Likewise, a piece of American literature employs the term "dropouts" to designate "young people who leave school without gaining a high school diploma" (Lamb and Markussen, 2011).

place). Further, we bring together the information regarding the regencies by means of Regional decrees of Regency Assignment. [5]

Moreover, given the availability of the addresses for both the directional schools and their merged complexes, we requested Google Maps Platform, through its Directions API, to calculate the shortest driving distance in Kilometers between each pair of directional schools and any of their merged complexes.

Our dataset includes a number of schools characteristics for 11,402 Italian secondary schools. We do not include in the sample those located in the regions of Valle d'Aosta and Molise, and provinces Trento and Bolzano.[6] We also exclude 489 schools that have been exposed to the policy change in the school year after (2011/2012) to the one observed (2010/2011) and knew about their next policy change by December 2010, as pointed out in section 2. This allows us to get rid of potential anticipation effects that may occur when there is a time gap between the policy announcement and the actual policy implementation. Table 1 details the variables with a brief description and the data sources.

4.1 Descriptive Statistics

The following figures aim at depicting the students dropouts phenomenon in the observed school year. Figure 1 and 2 give an overview on the dropouts, at the national average, per grade on lower and upper secondary schools. As expected, dropouts are higher in USS, which show a wider variability by grade. Indeed, while in the LSS the educational offers are homogeneous and the choice of school mostly depends on the geographical proximity to the school buildings, a numerous of different choices of USS is instead available to students. A poor orientation system may lead students to enroll in a school not suitable for their preferences or capabilities and then change school type during the first or second year, corresponding to the 9th and 10th grade.

The higher level of dropouts during the 4th year of USS, corresponding to the 12th grade, may depends on the fact that, in Italy, school attendance is compulsory until the age of 16 years old. As a result, since students on the 12th grade should be at least 17 years old, no law obliges them to stay in the classroom

[5] The detailed list of normative references is not reported here for the sake of brevity but is available from the author.

[6] Valle d'Aosta, Trento and Bolzano share a status of autonomous provinces and their data were not included in the national database. We were not able to find the Regional Decrees of Regency Assignment for the region Molise and, due to the impossibility to distinguish between under regent and not under regent schools, it is excluded from the sample.

Table 1: Data Description

Dependent Variables	Brief description	Source
Dropouts grade 6	Percentage of early leavers in the 6 grade (lower secondary school)	Miur- Scuola in Chiaro
Dropouts grade 7	Percentage of early leavers in the 7 grade (lower secondary school)	Miur- Scuola in Chiaro
Dropouts grade 8	Percentage of early leavers in the 8 grade (lower secondary school)	Miur- Scuola in Chiaro
Dropouts grade 9	Percentage of early leavers in the 9 grade (upper secondary school)	Miur- Scuola in Chiaro
Dropouts grade 10	Percentage of early leavers in the 10 grade (upper secondary school)	Miur- Scuola in Chiaro
Dropouts grade 11	Percentage of early leavers in the 11 grade (upper secondary school)	Miur- Scuola in Chiaro
Dropouts grade 12	Percentage of early leavers in the 12 grade (upper secondary school)	Miur- Scuola in Chiaro
Dropouts grade 13	Percentage of early leavers in the 13 grade (upper secondary school)	Miur- Scuola in Chiaro
Total dropouts per school	Sum of overall early leavers over total number of students	Our elaboration on MIUR data
Not admitted to the next class	Percentage of students not admitted to the next class per school	MIUR - Scuola in Chiaro
Treatment indicator		
Part - time SP (merged and/or under regent)	1 if merged and/or under regent, 0 othewise	Our elaboration on various sources
Running variable		
Total students per school	Sum of overall students per school in the school year 2010/2011	MIUR - Scuola in Chiaro
Other schools characteristics		
Number of complexes	Number of merged complexes per school	Our elaboration on MIUR data
School level	1 if upper secondary school, 0 if lower secondary school	MIUR - Scuola in Chiaro
Driving distance	Driving distance in Km of the shortest road linking merged schools	Google Direction API
USS School typology	1 if Lyceum, 2 if Technical Institute, 3 if Professional Institute	Our elaboration on MIUR data
Mountain municipality or small island	1 if the school is placed in mountain municipalities or small islands, 0 otherwise	Our elaboration on MIUR data

Source: The author

any longer.

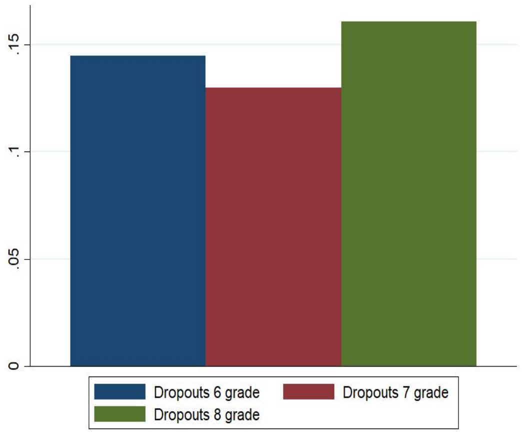

Figure 1: Dropouts (average) per grade in LSS. Source: Authors graph on MIUR - “Scuola in Chiaro” data

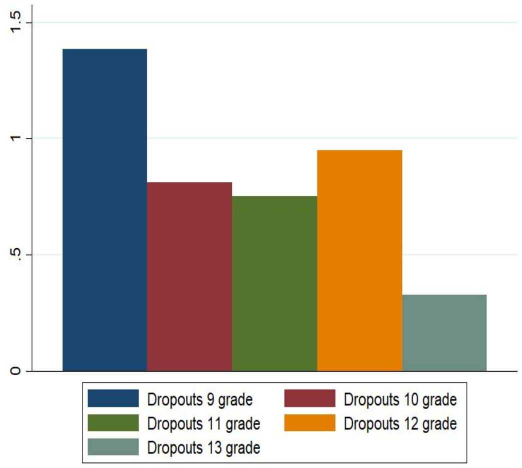

Figure 2: Dropouts (average) per grade in USS. Source: Authors graph on MIUR - “Scuola in Chiaro” data

Figure 3 plots the level of dropouts by treatment status. At a first glance, dropouts appear higher in treated schools.

Figure 4 details the level of dropouts by treatment status, taking into account the intensity of treatment. More specifically, the dropouts levels are plotted against the number of school merged complexes. In fact, we expect the more the school complexes that one single SP has to manage, the higher the complexity of his responsibilities. The picture actually shows higher levels of dropouts as the number of complexes increases but this does not apply on the right tale of the complexes distribution, where, however, we observe only a small number of observations that are characterized by such high number of merged complexes.

Figure 5 and 6 give information of the relationship between three variables: the level of dropouts, the treatment status and the forcing variable, namely the number of overall students enrolled in the given school. Both of them suggest that dropouts look higher in small and treated schools.

Table 2 reports the main descriptives for the LSS. Table 3 outlines the summary statistics for the USS. Both of them distinguish between treated and untreated (control) schools. We perform t tests on the equality of means for each dependent variable by treatment status. Results are never statistically significant and do not allow to reject the null hypothesis of equality.

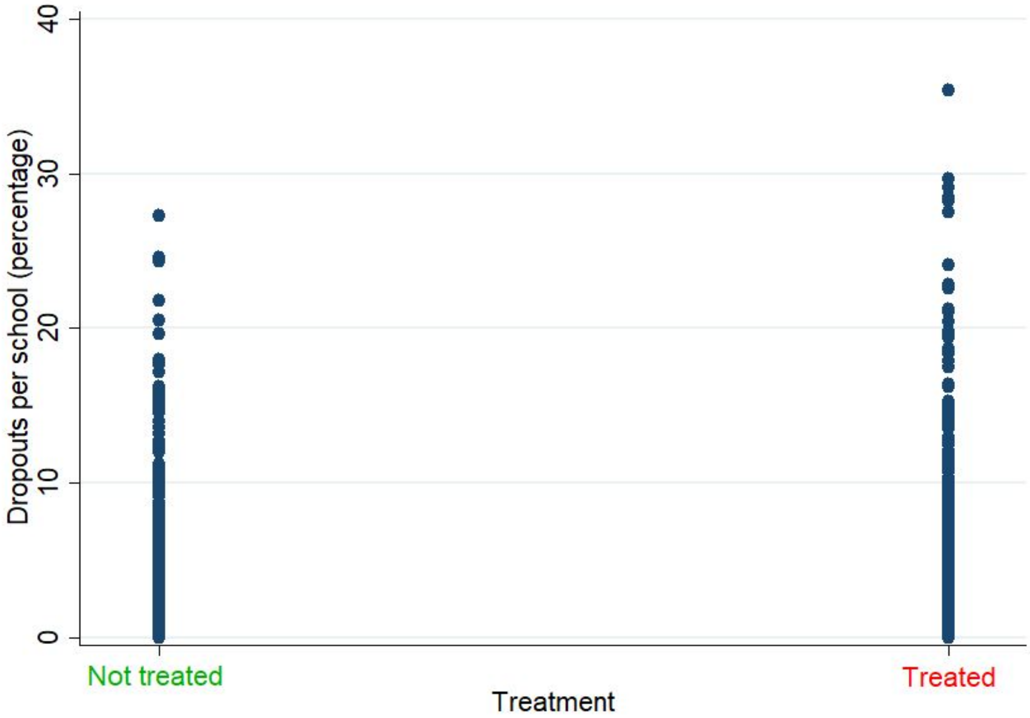

Figure 3: School dropouts Vs treatment (merged and/or under regent). Source: Authors graph

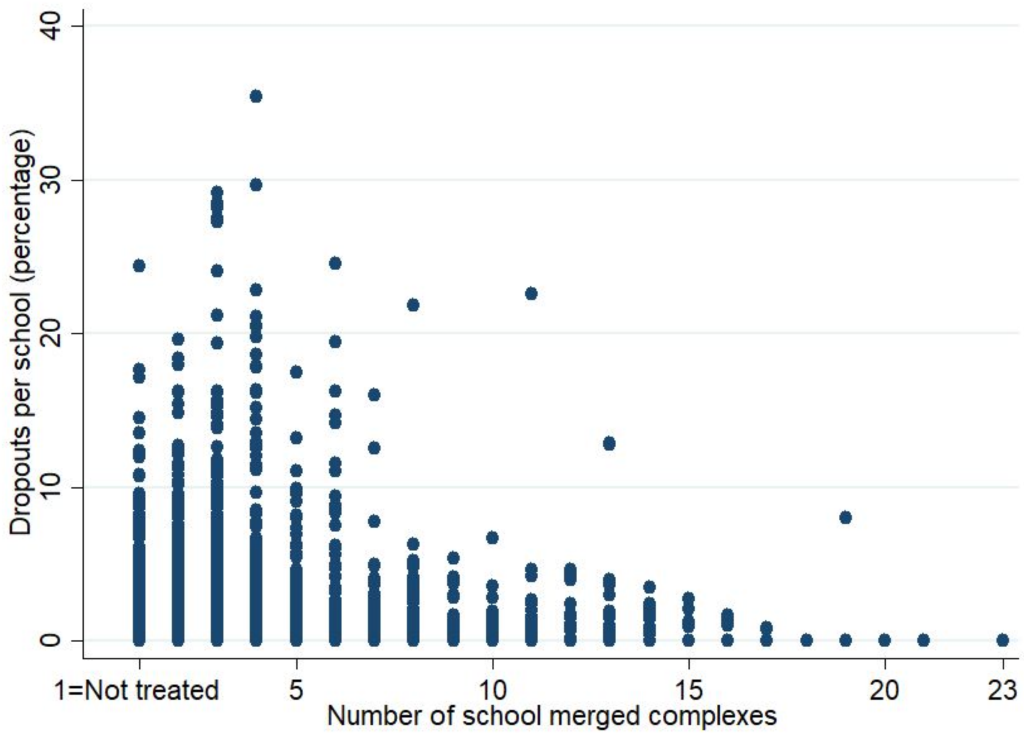

Figure 4: School dropouts Vs number of merged school complexes. Source: Authors graph

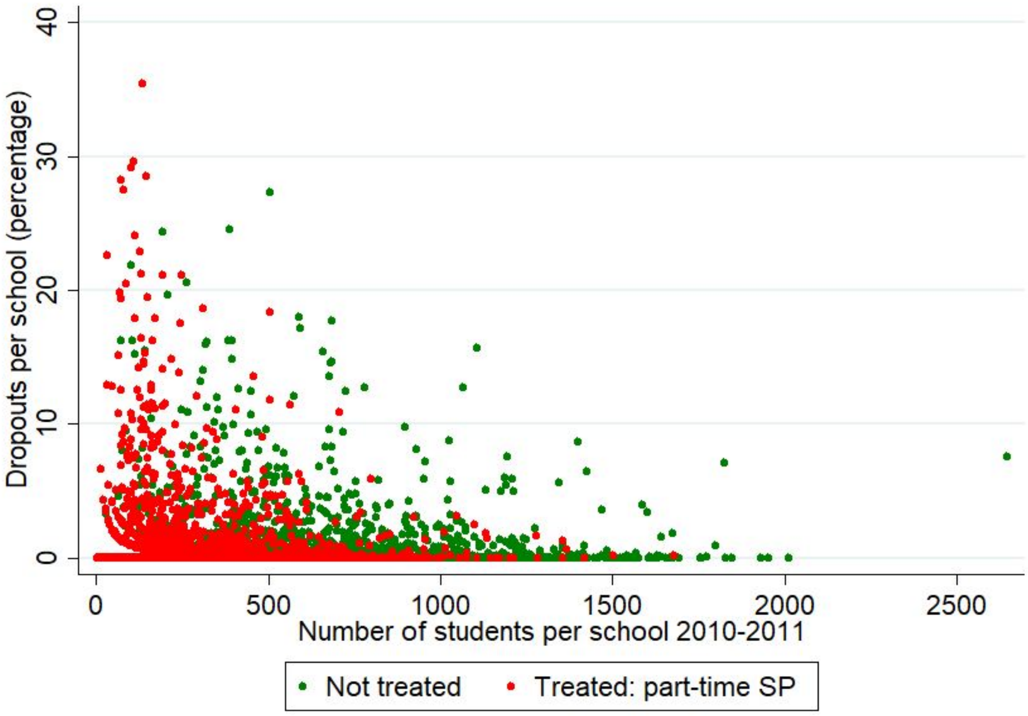

Figure 5: School dropouts Vs. number of students and treatment. Source: Authors graph

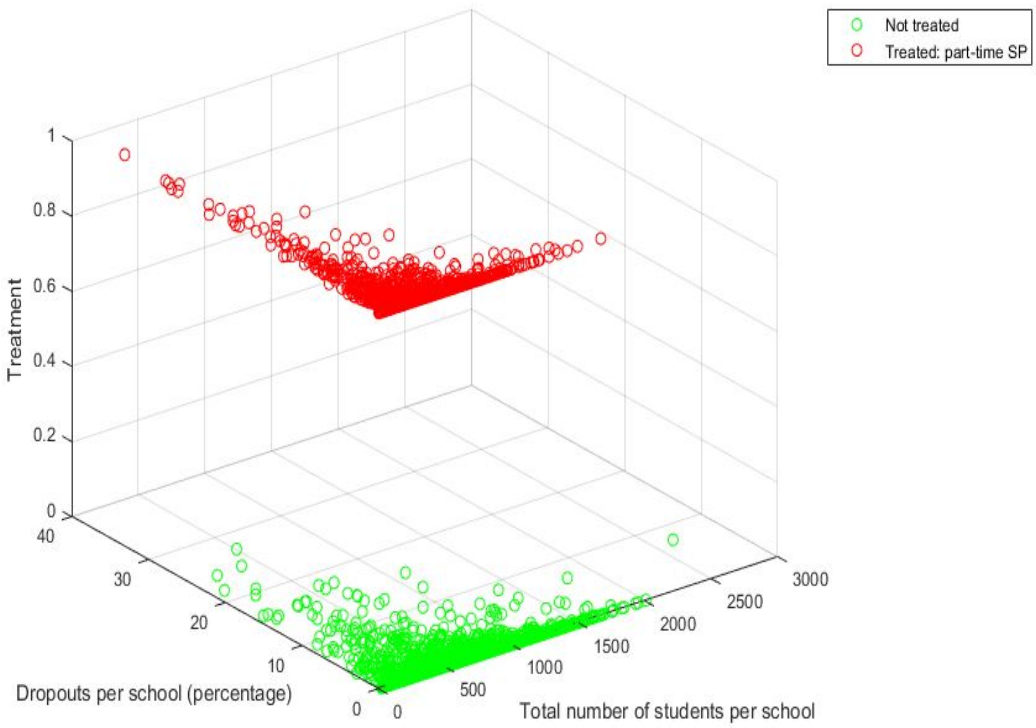

Figure 6: School dropouts Vs. number of students and treatment: 3D scatterplot. Source: Authors graph

Table 2: Summary statistics: Untreated vs treated LSS

Variable	Mean	Std. Dev.	Min.	Max.	N
Untreated					
Dropouts grade 6th	0.084	0.421	0	6.100	1710
Dropouts grade 7th	0.083	0.5	0	13.6	1710
Dropouts grade 8th	0.093	0.438	0	6	1712
Total dropouts per school	0.086	0.281	0	4.603	1707
Not admitted to the next class per school	4.799	4.357	0	68.3	1714
Treatment: part-time SP	0	0	0	0	1714
Total number of students enrolled	412.579	236.343	12	1149	1714
Driving distance from directional school	0	0	0	0	1714
Mountain municipality or small island	0.153	0.361	0	1	1714
Treated					
Dropouts grade 6th	0.078	0.735	0	27.3	4916
Dropouts grade 7th	0.069	0.598	0	25	4900
Dropouts grade 8th	0.108	0.727	0	18.2	4927
Total dropouts per school	0.087	0.453	0	12.903	4862
Not admitted to the next class per school	4.538	4.313	0	40	4952
Treatment: part-time SP	1	0	1	1	4952
Total number of students enrolled	175.203	137.492	2	910	4951
Driving distance from directional school	7.456	48.844	0	1233.191	4491
Mountain municipality or small island	0.299	0.458	0	1	4952

Source: Author elaboration

4.2 Graphical Analysis at the Cutoff

The following figures provide a graphical analysis aimed at showing intuitively and transparently any jumps across the threshold in the running variable.

Figure 7 explores the discontinuity around the threshold for the two outcomes of interest, both at the aggregate level for all schools and by school level. Figure 8 disentangles the volumes of dropouts by grade. Figure 9 studies the compliance of the treatment to the merging rule, showing a clear discontinuity at the cutoff. Although the level of compliance to the rule look high, the figure provide evidence of the occurrence of some fuzziness in the treatment compliance. Figure 10 studies the discontinuity with respect to the driving distance in kilometers from the directional school to the merged complexes, confirming the evidence on the great level of compliance to the merging rule.

Table 3: Summary statistics: untreated vs treated USS

Variable	Mean	Std. Dev.	Min.	Max.	N
Untreated					
Dropouts grade 9th	1.18	4.052	0	47.4	2376
Dropouts grade 10th	0.701	2.529	0	43.3	2382
Dropouts grade 11th	0.675	2.494	0	41.2	2380
Dropouts grade 12th	0.773	2.924	0	53.8	2373
Dropouts grade 13th	0.31	1.313	0	17.6	2364
Total dropouts per school	0.776	2.379	0	27.262	2329
Not admitted to the next class per school	10.915	7.76	0	60	2406
Treatment: part-time SP	0	0	0	0	2407
Total number of students enrolled	653.129	355.433	10	2648	2407
Driving distance to directional school	0	0	0	0	2407
Mountain municipality or small island	0.128	0.334	0	1	2407
Treated					
Dropouts grade 9th	1.463	5.266	0	59.1	2230
Dropouts grade 10th	0.909	3.727	0	52	2208
Dropouts grade 11th	0.818	3.32	0	68.8	2204
Dropouts grade 12th	1.102	4.418	0	56.3	2163
Dropouts grade 13th	0.35	1.961	0	36.8	2146
Total dropouts per school	0.985	3.106	0	35.419	2009
Not admitted to the next class per school	12.743	9.004	0	73.7	2328
Treatment: part-time SP	1	0	1	1	2329
Total number of students enrolled	281.445	214.854	9	1679	2328
Driving distance to directional school	8.041	44.491	0	1016.51	2059
Mountain municipality or small island	0.216	0.412	0	1	2329

Source: Author elaboration.

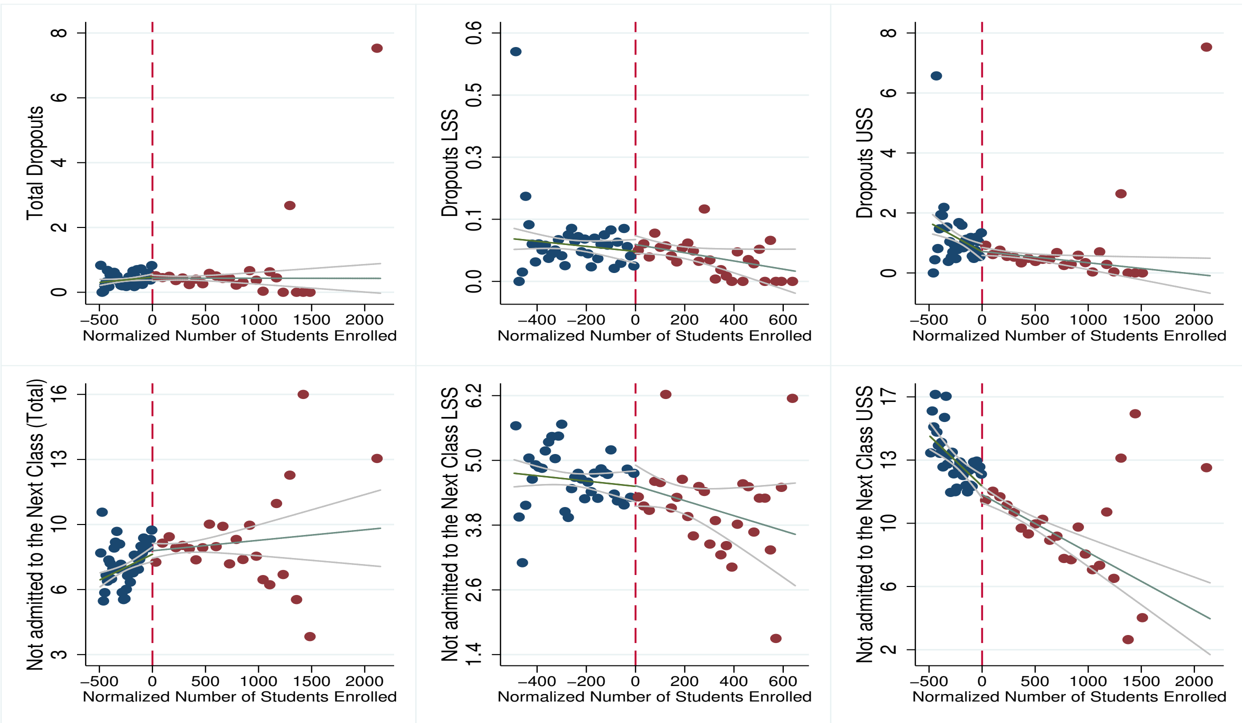

Figure 7: Dropouts and Not Admitted to the Next Class. Source: Authors graph

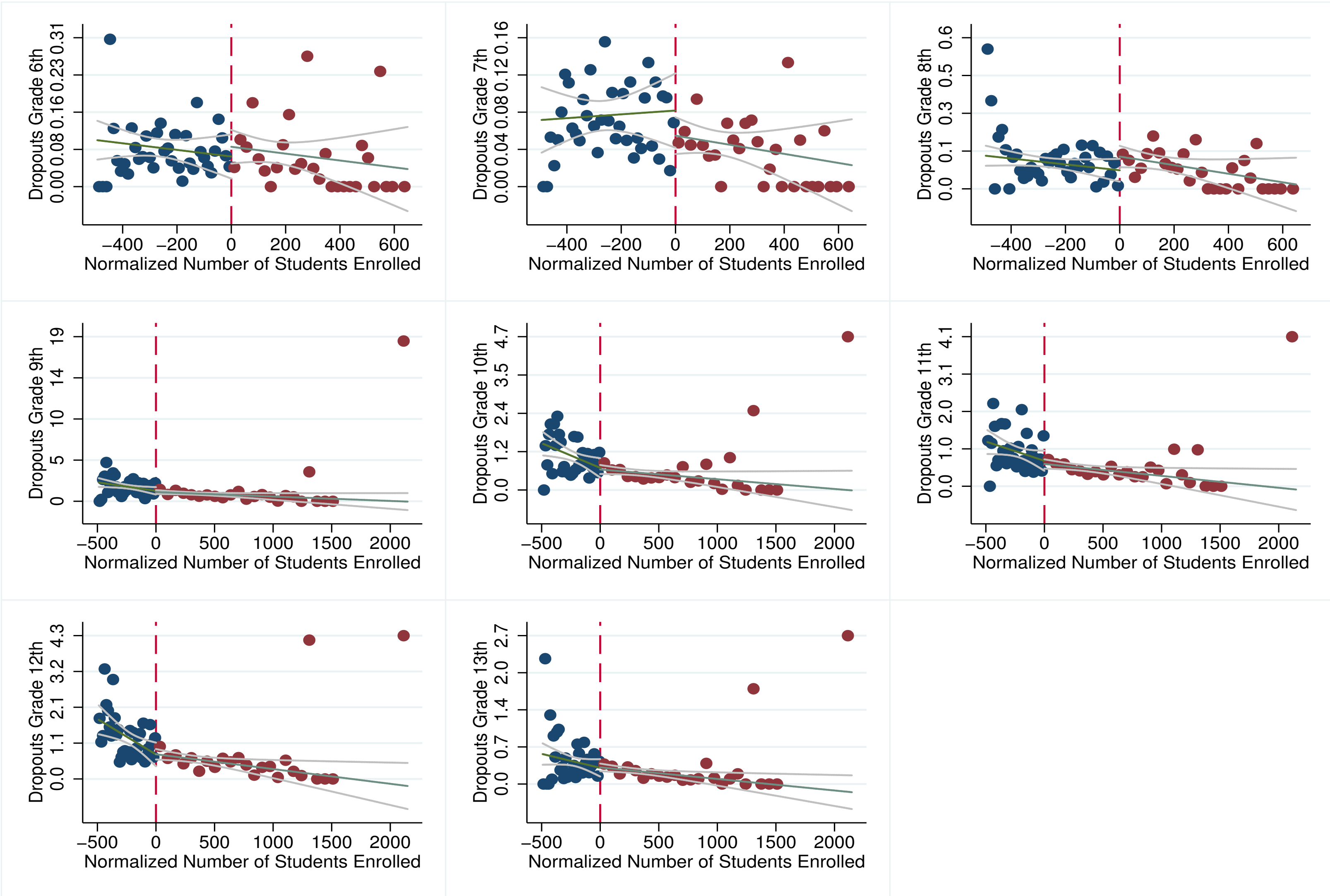

Figure 8: Dropouts per Grade. Source: Authors graph

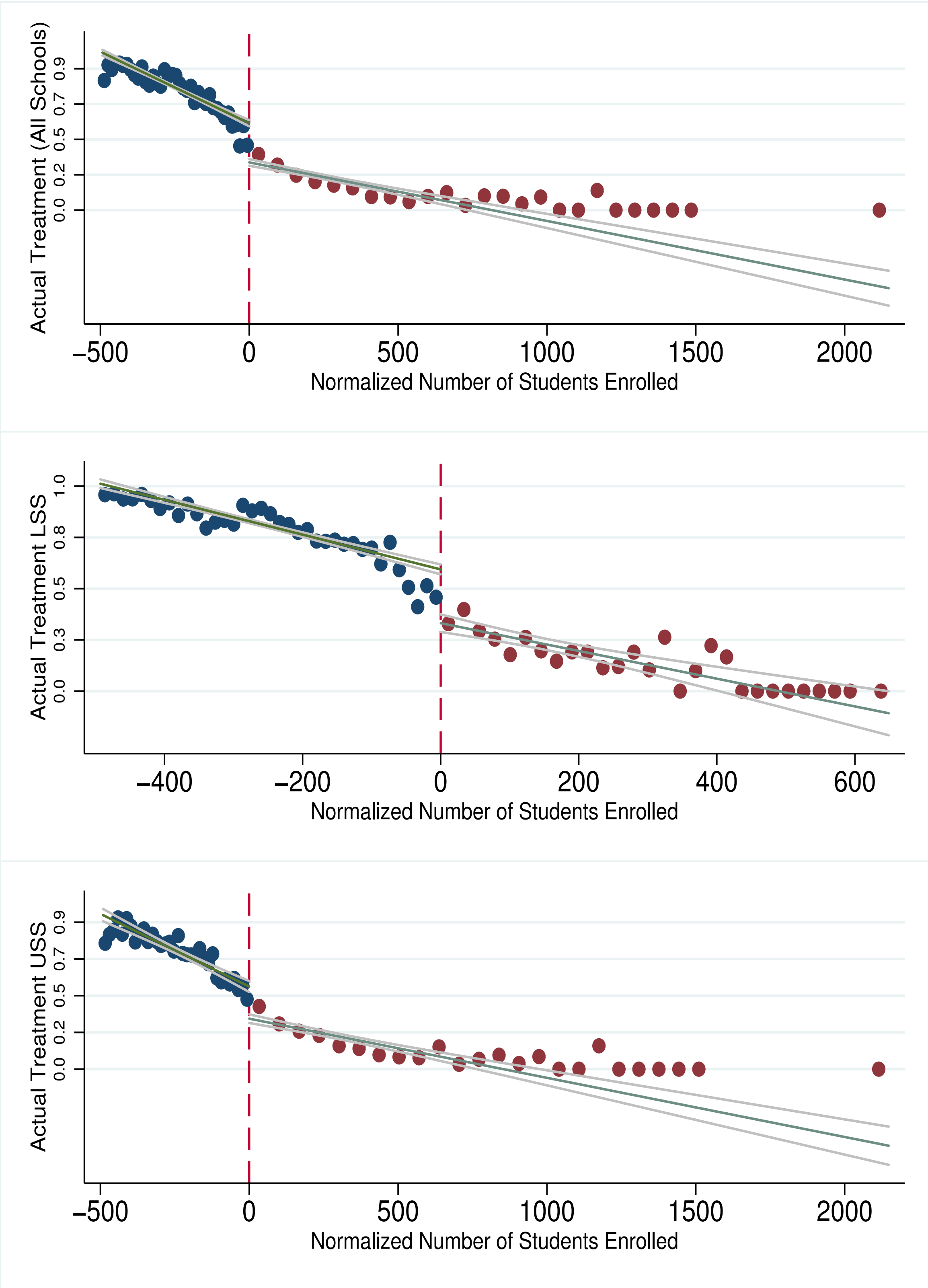

Figure 9: Treatment Compliance. Source: Authors graph

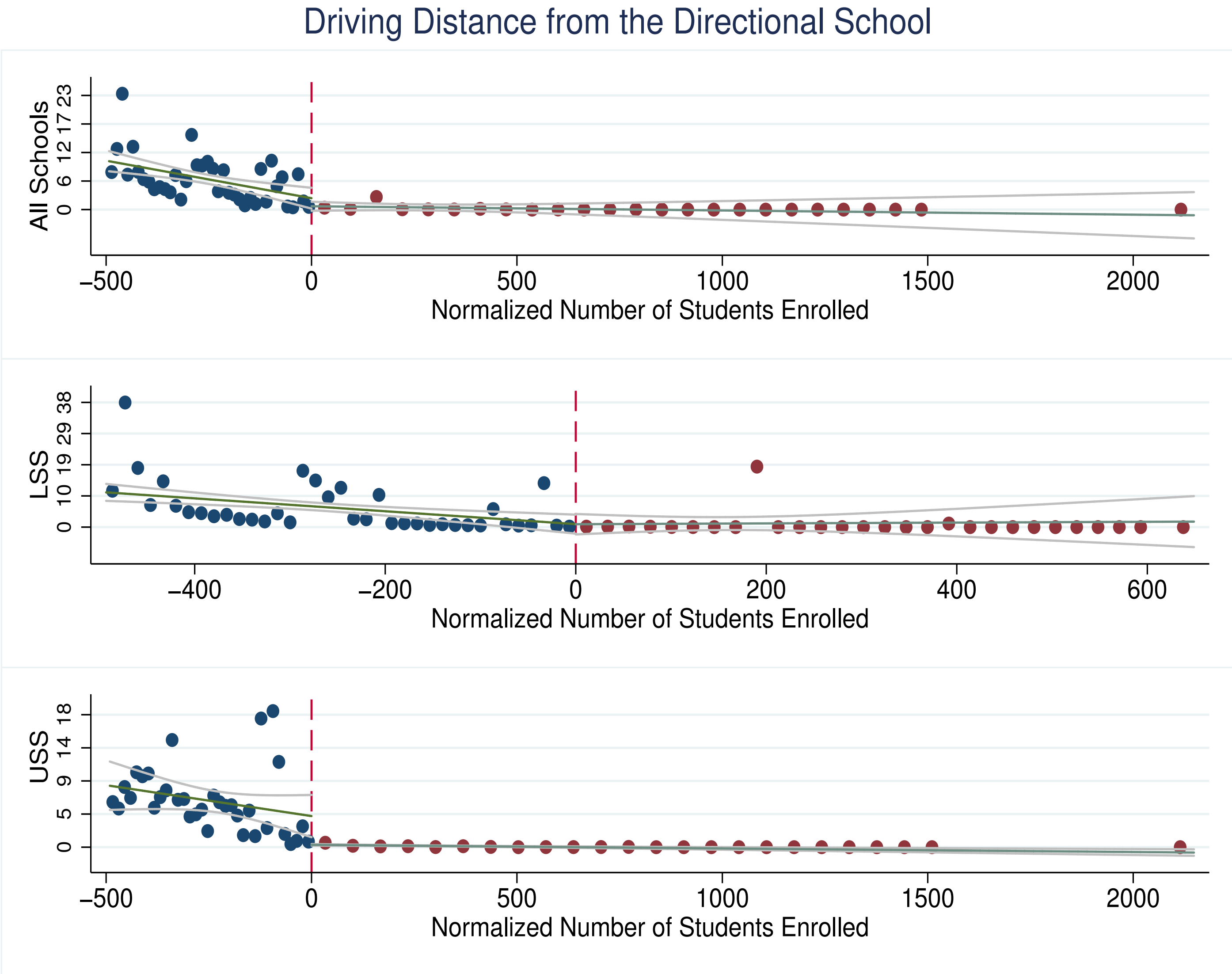

Figure 10: Driving Distance (Km) from the Directional School to the Merged Complexes. Source: Authors graph

5 Identification Strategy

To assess the consolidation policy impact on student outcomes, we implement a continuity-based local polynomial approximation Fuzzy Regression Discontinuity Design (fuzzy RDD hereafter). In the general RDD framework, all units in the sample receive a score, also known as running or forcing variable, and a treatment is assigned to those units whose score is above a known cutoff, while those units whose score is below the cutoff are used as the counterfactual (Hahn *et al.*, 2001).

Fuzzy RDD is a quasi-experimental method in which the probability of receiving treatment changes discontinuously across the threshold as a function of a running variable (Dai *et al.* 2018), and the compliance with treatment assignment is no longer perfect, as in the Sharp design. [7]

Since the eligibility rules were not perfectly enforced in the Italian school case, and some ineligible schools received the program while some eligible schools failed to receive it, the program eligibility assigned discontinuously based on a score and a cutoff, and the imperfect compliance with eligibility status, makes this policy evaluation design suitable for a Fuzzy RDD where the running variable is the number of students enrolled in a given school, and the treatment is being a merged and/or under regent complex.

Treated and control schools may be different. As suggested by Cattaneo *et al.* (2017), if some of the characteristics on which they differ are correlated with the outcomes of interest, a simple comparison of the two groups will be misleading. For example, it seems reasonable to assume the occurrence of a selection process into the treated group: the "worst schools" may not be chosen by new students and therefore experience a decrease in the number of enrolled, reaching ultimately the merger program. The "worst schools" therefore have a greater risk of ending up in the treated group and a possible increase in their dropouts levels would not only depend on the policy implementation but on the pre-existing limited quality of the schools.

In such situations, a Regression Discontinuity (RD) strategy can be used to isolate a treatment effect of interest from all other systematic differences between treated and control groups. In other words, the observations just above and just below the cutoff will tend to be comparable in terms of all characteris-

[7] In contrast to Sharp RD, in a Fuzzy RD design, the change in the probability of being treated at the cutoff is always less than one.

tics, and point estimates get rid of systematic observed and unobserved differences between the groups. As suggested by Calonico *et al.* (2018), modern RD application employ a low-order polynomial approximation (usually linear or quadratic) only around the cutoff, ruling out all other observations further away.[8]

Local polynomial methods estimate the chosen polynomials using only observations near the cutoff, separately for control and treatment observations. More formally, this approach uses only observations in the neighborhood of the threshold, essentially between $\bar{x}_-$ h and $\bar{x}_+$ h, where h is the given bandwidth. Moreover, within this bandwidth, a kernel function k(.) assigns a positive increasing weight to the observations depending on their proximity to the cutoff $\bar{x}$.[9]

Following Calonico *et al.* (2014, 2017), we choose the *p-th* order local polynomial estimator with the *q-th* order local polynomial bias correction, with triangular kernel function that assigns a proportionally higher weight to the observations closer to the cutoff. We also compute the optimal fuzzy RDD data-driven bandwidth for our sample.[10]

Yet, this approach can be viewed formally as a nonparametic local polynomial method, in which the fit is taken as an approximation of the unknown underlying regression functions within the bandwidth used, with a potential misspecification of the functional form of the regression function.

In the policy change focus of this paper, as common in practice, the treatment is assigned using different cutoff values for different subgroups of observations. In fact, as pointed out in section 2, while the cutoff is normally 500, it is reduced at 300 students in schools located in mountain areas and small islands. Given this multi-cutoff RD design, we follow the commonly used approach and normalize (or center) the running variable at zero, such that all schools face the same common cutoff value, and then apply the standard Fuzzy RDD routines to the normalized score. However, we also consider the two different group of schools, and then each cutoff, separately, to detect potential heterogeneous effects.

[8]Gelman and Imbens (2018) give some cautionary advices against using higher-order polynomial in RD designs since they might inappropriately put large weights on observations further away from the cutoff. Higher-order polynomials tend to produce over-fitting of the data and thus unreliable results near boundary points. Local constant fits ($p = 0$) exhibit some undesirable theoretical features and usually under-fit the data. In practice, the recommended choices are usually $p = 1$ or $p = 2$, though theory and practice considers other polynomial orders as well (Cattaneo *et al.*, 2017).

[9]A kernel function may be triangular (assigning a positive weight to all observation within the bandwidth h but declining symmetrically and linearly as the value of the forcing variable gets farther from the cutoff, becoming zero outside h), uniform (which gives zero weight to all observations with score outside the bandwidth but equal weight to all the observations within h) and Epanechnikov (which gives a quadratic decaying weighting to observations within h and zero weight to the rest)(Cattaneo *et al.*, 2017).

[10]We implement this two-step procedure with the the Stata routine `rdrobust` which reports the correct standard errors. We run bandwidth selection with the Stata command `rdbwselect`, with the option `msetwo` for MSE - optimal point estimation using a different bandwidth on the two sides of the cutoff.

In practice we estimate the following two equations. In the first-stage equation the outcome variable is a dummy that equals value 1 if the school is actually treated, 0 otherwise:

$$ActualTreatment_i = \delta_0 + \delta_1 PredictedTreatment_i + \delta_2(a) + \epsilon_i, \tag{1}$$

where *Predicted Treatment* denotes the treatment eligibility established by the D.P.R. 233/1998 and reviewed in section 2 ($PredictedTreatment = 1(a < 0)$). $\delta_2(a)$ is a polynomial of the running variable in the continuous measure of number of students enrolled in a given school.[11]

In the second equation we estimate:

$$y_{ji} = \gamma_0 + \gamma_1 ActualTreatment_i + \gamma_2(a) + u_i, \tag{2}$$

where y_{ji} are the set of j dependent variables outlined in section 4 for the school i, $\gamma_2(a)$ is again a continuous function of the running variable and the $ActualTreatment_i$ is the treatment status. Estimation results follow in the next session.

One potential concern on the validity of the chosen method is the continuity of the forcing variable at the cutoff. In our setting, where the running variable is the number of students in a given school, this means that schools cannot systematically manipulate the number of students enrolled. Following Cattaneo *et al.* (2017), we test the continuity of the normalized forcing variable by means of a number density tests that are reported in table 3.11 in appendix, along with the estimated density plots and histograms. The value of the statistic used to test is 0.04913 and the associated p-value is 0.6232, for all schools of the sample. This suggests that, under the continuity-based approach, we fail to reject the null hypothesis of no difference in the density of treated and control schools at the cutoff, consistent with the identification assumption that treatment assignment around the discontinuity was "as good as random" (Amarante *et al.*, 2016). Figure 11 and 12 provide a graphical representation of the continuity in density tests, exhibiting both the estimated density (fig. 11) and the histogram of the data (fig. 12).

[11] We do not include covariates because the available data on other schools characteristics would lead to a decrease in the sample size. However, despite the inclusion of covariates is intended to increase the precision of the RD estimates, Calonico *et al.* (2018) note that there is no existing justification for using additional covariates for identification, estimation, or inference purposes, employing only continuity/smoothness conditions at the cutoff. They also highlight the fact that this has led, in empirical practice, to the proliferation of *ad hoc* covariate adjustments that may reduce the transparency of the estimation and result in noncomparable, or even inconsistent, estimators.

Table 4: Student dropouts by school type: LSS and USS. Fuzzy RD estimates.

	(1)	(2)	(3)
VARIABLES	Dropouts LSS	Dropouts LSS	Dropouts LSS
RD Estimate	-0.0642	-0.547	-0.499
Robust 95% CI	[-.538 -.192]	[-3.439 -1.483]	[-2.911 - 1.99]
Kernel Type	Triangular	Triangular	Triangular
Observations	6569	6569	6569
Conventional Std. Error	0.142	1.133	1.147
Conventional p-value	0.650	0.629	0.663
Robust p-value	0.353	0.436	0.712
Order Loc. Poly. (p)	0.000	1.000	2.000
Order Bias (q)	1.000	2.000	3.000
	(1)	(2)	(3)
VARIABLES	Dropouts USS	Dropouts USS	Dropouts USS
RD Estimate	1.532	7.942	33.79
Robust 95% CI	[-2.1 - 6.541]	[-20.234 - 47.991]	[-494.97 - 636.006]
Kernel Type	Triangular	Triangular	Triangular
Observations	4338	4338	4338
Conventional Std. Error	1.759	15.225	259.022
Conventional p-value	0.384	0.602	0.896
Robust p-value	0.314	0.425	0.807
Order Loc. Poly. (p)	0.000	1.000	2.000
Order Bias (q)	1.000	2.000	3.000

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors clustered at the province level.

We run the same tests distinguishing between the school levels. We find no discontinuity in the density of treated and control USS at the cutoff, while results for the subsample of LSS provide evidence of a sort of manipulation at 10% level of confidence.

6 Results

Obtained estimation results show that the treatment status hardly affected students outcomes. In fact, table 4 and 5 suggest that program exposure is scarcely associated to statistically significant variation in students dropouts and students that fail to pass to the next class. In fact, only the percentage of students not admitted to the next class looks higher by 24.94 percentage points in the treated USS schools, although this results is not robust to different choices of local polynomial order.[12]

[12] Even though results are not reported here, uniform and epanechnikov kernel functions have been tried too. Results do not change.

Table 5: Non admitted to the next class by school type: LSS and USS. Fuzzy RD estimates.

	(1)	(2)	(3)
VARIABLES	Not-admitted LSS	Not-admitted LSS	Not-admitted LSS
RD Estimate	1.738	10.77	-4.789
Robust 95% CI	[-4.782 - 11.273]	[-36.254 - 78.236]	[-37.693 - 20.125]
Kernel Type	Triangular	Triangular	Triangular
Observations	6665	6665	6665
Conventional Std. Error	3.526	26.433	13.554
Conventional p-value	0.622	0.684	0.724
Robust p-value	0.428	0.472	0.551
Order Loc. Poly. (p)	0.000	1.000	2.000
Order Bias (q)	1.000	2.000	3.000
	(1)	(2)	(3)
VARIABLES	Not-admitted USS	Not-admitted USS	Not-admitted USS
RD Estimate	24.94**	84.06	164.9
Robust 95% CI	[4.358 - 80.545]	[-238.347 - 451.248]	[-1174.776 - 1429.352]
Kernel Type	Triangular	Triangular	Triangular
Observations	4733	4733	4733
Conventional Std. Error	17.416	153.117	596.655
Conventional p-value	0.152	0.583	0.782
Robust p-value	0.029	0.545	0.848
Order Loc. Poly. (p)	0.000	1.000	2.000
Order Bias (q)	1.000	2.000	3.000

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors clustered at the province level.

Table 6 and 7 explore the impact of the treatment exposure on student dropouts by cohort and school type. Only in the 8th grade the merger policy seems to play a role in diminishing the dropouts phenomenon. However, this result is not robust to different choice of local polynomial order and may be biased by the evidence of manipulation given by the density test of the running variable for the LSS reported in table 11 in appendix.

6.1 Heterogeneous Treatment Effects

A common question of interest in a policy evaluation exercise is "which groups are the most affected by the treatment exposure?" A standard way to address this inquiry is to look at heterogeneity in treatment effects with respect to the baseline sample characteristics.

We first look at potential differences with regard to geographical school characteristics, which imply different cutoffs on the running variable as well. We therefore conduct the estimation exercise only for schools in mountain municipalities and small islands, whose cutoff determining the treatment status is

Table 6: Student dropouts by cohort: LSS

	(1)	(2)	(3)
VARIABLES	Dropouts 6th grade	Dropouts 6th grade	Dropouts 6th grade
RD Estimate	0.146	0.788	0.756
Robust 95% CI	[-.248 - .798]	[-1.706 - 4.114]	[-1.715 - 3.131]
Observations	6625	6625	6625
Conventional Std. Error	0.219	1.404	1.156
Conventional p-value	0.505	0.574	0.513
Robust p-value	0.302	0.417	0.567
VARIABLES	Dropouts 7th grade	Dropouts 7th grade	Dropouts 7th grade
RD Estimate	0.0630	-0.0189	0.130
Robust 95% CI	[-.335 - .475]	[-2.313 - 2.001]	[-3.808 - 3.943]
Observations	6609	6609	6609
Conventional Std. Error	0.158	0.933	1.764
Conventional p-value	0.690	0.984	0.941
Robust p-value	0.736	0.888	0.973
VARIABLES	Dropouts grade 8th	Dropouts grade 8th	Dropouts grade 8th
RD Estimate	-0.501**	-2.527	-2.327
Robust 95% CI	[-1.846 - -.054]	[-17.147 - 8.71]	[-9.94 - 4.819]
Observations	6638	6638	6638
Conventional Std. Error	0.352	6.025	3.537
Conventional p-value	0.154	0.675	0.511
Robust p-value	0.038	0.523	0.496
Kernel Type	Triangular	Triangular	Triangular
Order Loc. Poly. (p)	0.000	1.000	2.000
Order Bias (q)	1.000	2.000	3.000

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors clustered at the province level.

Table 7: Student dropouts by cohort: USS

	(1)	(2)	(3)
VARIABLES	Dropouts grade 9th	Dropouts grade 9th	Dropouts grade 9th
RD Estimate	1.776	9.453	32.13
Robust 95% CI	[-4.591 - 9.532]	[-19.058 - 49.953]	[-212.83 - 300.722]
Observations	4605	4605	4605
Conventional Std. Error	2.824	15.657	117.212
Conventional p-value	0.529	0.546	0.784
Robust p-value	0.493	0.380	0.737
VARIABLES	Dropouts grade 10th	Dropouts grade 10th	Dropouts grade 10th
RD Estimate	0.843	0.643	14.70
Robust 95% CI	[-3.219 - 4.61]	[-13.575 - 15.95]	[-216.493 - 287.126]
Observations	4589	4589	4589
Conventional Std. Error	1.523	6.337	114.043
Conventional p-value	0.580	0.919	0.897
Robust p-value	0.728	0.875	0.783
VARIABLES	Dropouts grade 11th	Dropouts grade 11th	Dropouts grade 11th
RD Estimate	1.420	11.95	43.51
Robust 95% CI	[-1.982 - 6.242]	[-21.952 - 59.04]	[-327.06 - 483.219]
Observations	4583	4583	4583
Conventional Std. Error	1.665	18.196	184.557
Conventional p-value	0.394	0.511	0.814
Robust p-value	0.310	0.369	0.706
VARIABLES	Dropouts grade 12th	Dropouts grade 12th	Dropouts grade 12th
RD_Estimate	1.192	-0.113	1.109
Robust 95% CI	[-3.957 - 6.074]	[-23.68 - 19.393]	[-64.4 - 65.42]
Observations	4535	4535	4535
Conventional Std. Error	1.958	9.148	28.783
Conventional p-value	0.543	0.990	0.969
Robust p-value	0.679	0.845	0.988
VARIABLES	Dropouts grade 13th	Dropouts grade 13th	Dropouts grade 13th
RD Estimate	0.0821	-0.823	-2.498
Robust 95% CI	[-2.07 - 1.701]	[-7.997 - 4.778]	[-37.862 - 28.769]
Observations	4509	4509	4509
Conventional Std. Error	0.720	2.645	14.745
Conventional p-value	0.909	0.756	0.865
Robust p-value	0.848	0.621	0.789
Kernel Type	Triangular	Triangular	Triangular
Order Loc. Poly. (p)	0.000	1.000	2.000
Order Bias (q)	1.000	2.000	3.000

Note: *** p¡0.01, ** p¡0.05, * p¡0.10. Standard errors clustered at the province level.

set at 300 students. Table 3.8 shows the results for the two dependent variables of interest and by school level, which are suggestive of a statistically insignificant effect of the program on student outcomes.

Furthermore, we restrict the sample of treated school to those far away from the directional school at least 10 kilometers. Results are presented in table 9. Even though findings are not robust to the chosen local polynomial order, the local estimates show a negative impact of the program exposure on both dependent variables: student dropouts and students that fail to pass to the next class seem higher in treated and far away schools.[13]

Finally, we focus on the different categories of USS. In fact in the Italian system, after the LSS path, a student faces different school choices, which vary from Lyceums to Technical and Professional Institutes, Music Conservatory, Academy of Arts and National Dance Academy. Given the available data, a robust sample size is possible only for Lyceums, Technical and Professional Institutes. Results reported in table 10 are not suggestive of any significant heterogeneous effect with respect to the USS school typology.

[13] We conducted the estimation disentangling by school level and the USS seem the ones that tow the overall effect.

Table 8: Treatment effect in mountain municipalities and small islands

Lower Secondary Schools						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Dropouts	Dropouts	Dropouts	Not admitted	Not admitted	Not admitted
RD Estimate	-0.645	-0.266	-0.262	-5.815	-6.331	-2.298
Robust 95% CI	[-2.179 - .526]	[-.654 - .18]	[-.661 - .166]	[-34.033 - 10.188]	[-20.788 - 5.436]	[-8.948 - 5.027]
Kernel Type	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular
Observations	1697	1697	1697	1744	1744	1744
Conventional Std. Error	0.548	0.194	0.195	9.013	5.740	3.321
Conventional p-value	0.239	0.170	0.178	0.519	0.270	0.489
Robust p-value	0.231	0.265	0.240	0.291	0.251	0.582
Order Loc. Poly. (p)	0.000	1.000	2.000	0.000	1.000	2.000
Order Bias (q)	1.000	2.000	3.000	1.000	2.000	3.000
Upper Secondary Schools						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Dropouts	Dropouts	Dropouts	Not admitted	Not admitted	Not admitted
RD Estimate	5.169	-1.323	-1.568	-110.9	-15.99	-10.20
Robust 95% CI	[-7.313 - 39.221]	[-12.357 - 11.221]	[-12.204 - 9.831]	[-1477.815 - 2583.697]	[-70.381 - 51.669]	[-46.377 - 27.578]
Kernel Type	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular
Observations	707	707	707	810	810	810
Conventional Std. Error	9.526	5.115	5.015	867.551	26.681	16.278
Conventional p-value	0.587	0.796	0.754	0.898	0.549	0.531
Robust p-value	0.179	0.925	0.833	0.594	0.764	0.618
Order Loc. Poly. (p)	0.000	1.000	2.000	0.000	1.000	2.000
Order Bias (q)	1.000	2.000	3.000	1.000	2.000	3.000

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors clustered at the province level.

Table 9: Treated school far away from the directional school at least 10 Km

	(1)	(2)	(3)
VARIABLES	Dropouts	Dropouts	Dropouts
RD Estimate	2.305*	7.921	28.92
Robust 95% CI	[-.416 - 8.628]	[-16.61 - 46.485]	[-251.717 - 316.137]
Observations	7412	7412	7412
Conventional Std. Error	1.952	14.203	129.387
Conventional p-value	0.238	0.577	0.823
Robust p-value	0.075	0.353	0.824
VARIABLES	Not admitted	Not admitted	Not admitted
RD Estimate	27.36**	212.0	255.4
Robust 95% CI	[3.647 - 97.288]	[-2342.111 - 3216.67]	[-3753.949 - 4080.582]
Observations	7722	7722	7722
Conventional Std. Error	21.343	1237.5	1776.4
Conventional p-value	0.200	0.864	0.886
Robust p-value	0.035	0.758	0.935
Kernel Type	Triangular	Triangular	Triangular
Order Loc. Poly. (p)	0	1	2
Order Bias (q)	1	2	3

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors clustered at the province level.

Table 10: Estimation results by USS typology

Lyceums						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Dropouts	Dropouts	Dropouts	Not admitted	Not admitted	Not admitted
RD Estimate	0.163	5.026	3.090	5.376	15.95	24.5
Robust 95% CI	[-2.015 - 2.022]	[-60.614 - 80.449]	[-64.082 - 87.624]	[-2.044 - 22.458]	[-26.849 - 80.272]	[-110.395 - 163.75]
Observations	1539	1539	1539	1635	1635	1635
Conventional Std. Error	0.744	31.062	33.759	5.46	24.05	62.098
Conventional p-value	0.827	0.871	0.927	0.325	0.507	0.693
Robust p-value	0.997	0.783	0.761	0.102	0.328	0.703
Professional Institutes						
RD Estimate	0.407	15.43	5.997	16.3	-22.22	-8.891
Robust 95% CI	[-21.314 - 20.425]	[-325.557 - 315.894]	[-69.996 - 88.214]	[-57.932 - 159.23]	[-297.223 - 268.948]	[-99.509 - 90.06]
Observations	1079	1079	1079	1227	1227	1227
Conventional Std. Error	8.224	140.143	36.166	47.08	124.721	42.584
Conventional p-value	0.96	0.912	0.868	0.729	0.859	0.835
Robust p-value	0.967	0.976	0.821	0.361	0.922	0.922
Technical Institutes						
RD_Estimate	-0.157	0.453	2.481	6.882	32.12	10.05
Robust 95% CI	[-4.256 - 2.948]	[-9.95 - 14.033]	[-15.224 - 22.854]	[-6.599 - 34.134]	[-122.505 - 219.794]	[-62.35 - 75.618]
Observation	1516	1516	1516	1635	1635	1635
Conventional Std. Error	1.441	5.247	8.639	9.035	72.763	31.203
Conventional p-value	0.913	0.931	0.774	0.446	0.659	0.747
Robust p-value	0.722	0.739	0.695	0.185	0.577	0.851
Kernel Type	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular
Order Loc. Poly. (p)	0	1	2	0	1	2
Order Bias (q)	1	2	3	1	2	3

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors clustered at the province level.

7 Final Remarks and Discussion

Starting from the crucial role of the human capital in the process of economic growth, we aimed to assess the impact of the consolidation process that involved the Italian Secondary Schools - the main "producers" of human capital. We exploited the fuzzy discontinuity in treatment regime induced by the number of students enrolled in a given school to evaluate the impact of mergers on two categories of student dropout behaviour: voluntary dropouts and grade retention.

Estimation results of a continuity-based local polynomial approximation Fuzzy RDD show that the program exposure is scarcely associated to statistically significant variation in students dropouts and failure to progress. In fact, only the percentage of students not admitted to the next class looks higher by 24.94 percentage points in the treated USS schools. We also find evidence of heterogeneous effects with respect to the driving distance from directional schools to merged complexes. Indeed, the student dropout behaviour seems higher in treated schools far away at least 10 Km from the directional schools. This provides an insight on the potential causality channels that may drive the treatment effect. Indeed, the SP responsibilities appear substantially aggravated with the program exposure and the geographical distance from the merged schools he or she is in charge to run appears as an additional cost for the SP that contribute to isolate the merged school complexes, whose school-specific needs are not satisfied. Thus, the school consolidation process seems as a cost-saving policies from a public finance point of view that may fail in considering the indirect costs arising in term of poorer school performance, which may later produce labor market inequalities due to losses in human capital accumulation.

School merger programs are not limited to the Italian case but have been embraced by many other countries, such as China (Mo *et al.*, 2012), United States (Logan, 2018), Denmark (Beuchert *et al.*, 2018), and Netherlands (De Haan *et al.*, 2016). Thus, we added to the relevant literature by providing some evidence on the impact of such consolidation policies on student achievement in an additional educational framework.

The analysis presents some limitations. First, the effect of these policy changes on student performance may depend on the years of exposure to the consolidation program. Since we do not observe multiple periods, we are not able to explore this possibility. In addition, we do not have any information on SP characteristics, such as tenure or management skills, and student cognitive and non-cognitive skills, that the existing literature claims as a determinant of school performance.

Finally, the applied methodology produces estimations of treatment effect that are very local in nature and tend to have a little external validity. However, compared to more conventional quasi-experimental methods, such as the Differences in Differences approach, the Local Average Treatment Effect, also known as LATE, resulting from the RDD estimation, has substantially a higher internal validity and is less sensitive to boundary-related problems and outliers.

References

[1] Aaronson, D., Barrow, L., & Sander, W. (2007). Teachers and student achievement in the Chicago public high schools. Journal of labor Economics, 25(1), 95-135.

[2] Amarante, V., Manacorda, M., Miguel, E., & Vigorito, A. (2016). Do cash transfers improve birth outcomes? Evidence from matched vital statistics, program, and social security data. American Economic Journal: Economic Policy, 8(2), 1-43.

[3] Angrist, J. D., & Pischke, J.-S. (2009). Mostly harmless econometrics: An empiricist's companion. Princeton: Princeton University Press.

[4] Barro, R. J. (2001). Human capital and growth. American economic review, 91(2), 12-17.

[5] Beuchert, L., Humlum, M. K., Nielsen, H. S., & Smith, N. (2018). The short-term effects of school consolidation on student achievement: Evidence of disruption?. Economics of Education Review.

[6] Bloom, N., Lemos, R., Sadun, R., & Van Reenen, J. (2015). Does management matter in schools?. The Economic Journal, 125(584), 647-674.

[7] Besley, T., & Coate, S. (2003). Centralized versus decentralized provision of local public goods: a political economy approach. Journal of public economics, 87(12), 2611-2637.

[8] Branch, G. F., Hanushek, E. A., & Rivkin, S. G. (2012). Estimating the effect of leaders on public sector productivity: The case of school principals (No. w17803). National Bureau of Economic Research.

[9] Boffa, F., Piolatto, A., & Ponzetto, G. A. (2015). Political centralization and government accountability. The Quarterly Journal of Economics, 131(1), 381-422.

[10] Calonico, S., Cattaneo, M. D., & Titiunik, R. (2014). Robust nonparametric confidence intervals for regression-discontinuity designs. Econometrica, 82(6), 2295–2326.

[11] Calonico, Cattaneo, Farrell & Titiunik (2018): Regression Discontinuity Designs Using Covariates, Review of Economics and Statistics, forthcoming.

[12] Calonico, S., M.D. Cattaneo, Farrell, M. H., & Titiunik, R. (2017). rdrobust: software for regression-discontinuity designs. Stata Journal, 17, 372-404.

[13] Cattaneo, M. D., Idrobo, N., & Titiunik, R. (2017). A Practical Introduction to Regression Discontinuity Designs: Part I.

[14] Cattaneo, M. D., Idrobo, N., & Titiunik, R. (2018). A Practical Introduction to Regression Discontinuity Designs: Volume II.

[15] Cattaneo, M. D., Titiunik, R., & Vazquez-Bare, G. (2017). Comparing inference approaches for RD designs: A reexamination of the effect of head start on child mortality. Journal of Policy Analysis and Management, 36(3), 643-681.

[16] Clark, D., Martorell, P., & Rockoff, J. (2009). School Principals and School Performance. Working Paper 38. National Center for Analysis of longitudinal data in Education research.

[17] Coelli, M., & Green, D. A. (2012). Leadership effects: School principals and student outcomes. Economics of Education Review, 31(1), 92-109.

[18] Cullen, J. B., & Mazzeo, M. J. (2008). Implicit performance awards: An empirical analysis of the labor market for public school administrators. University of California, San Diego (December).

[19] Dai, F., Cai, F., & Zhu, Y. (2018). Returns to Higher Education in China: Evidence from the 1999 Higher Education Expansion Using Fuzzy Regression Discontinuity (No. 11735). Institute for the Study of Labor (IZA).

[20] De Haan, M., Leuven, E., & Oosterbeek, H. (2016). School consolidation and student achievement. The Journal of Law, Economics, and Organization, 32(4), 816-839.

[21] EUROSTAT - Statistic Explained https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Early_leaver_from_education_and_training. Accessed October 2018.

[22] Fontana, A. (2008). La rete scolastica: un modello per il numero di studenti per classe nella scuola primaria e secondaria di I grado. In: Paper presentato alla XX Conferenza della Società italiana di economia pubblica. Pavia, settembre.

[23] Galiani, S., Gertler, P., & Schargrodsky, E. (2008). School decentralization: Helping the good get better, but leaving the poor behind. Journal of public economics, 92(10-11), 2106-2120.

[24] Gelman, A., & Imbens, G. (2018). Why high-order polynomials should not be used in regression discontinuity designs. Journal of Business & Economic Statistics, 1-10.

[25] Google Maps Platform - Directions API https://developers.google.com/maps/documentation/javascript/directions.

[26] Grissom, J. A. (2011). Can good principals keep teachers in disadvantaged schools? Linking principal effectiveness to teacher satisfaction and turnover in hard-to-staff environments. Teachers College Record, 113(11), 2552-2585.

[27] Grissom, J. A., Kalogrides, D., & Loeb, S. (2015). Using student test scores to measure principal performance. Educational Evaluation and Policy Analysis, 37(1), 3-28.

[28] Grissom, J. A., & Loeb, S. (2011). Triangulating principal effectiveness: How perspectives of parents, teachers, and assistant principals identify the central importance of managerial skills. American Educational Research Journal, 48(5), 1091-1123.

[29] Hahn, J., Todd, P., & Van der Klaauw, W. (2001). Identification and estimation of treatment effects with a regression-discontinuity design. Econometrica, 69(1), 201-209.

[30] Hallinger, P., & Heck, R. H. (1998). Exploring the principal's contribution to school effectiveness: 1980-1995. School effectiveness and school improvement, 9(2), 157-191.

[31] Hanushek, Eric A., and Dennis D. Kimko (2000). Schooling, labor force quality, and the growth of nations. American Economic Review 90,no.5 (December):1184-1208.

[32] Hanushek, E. A., Lavy, V., & Hitomi, K. (2008). Do students care about school quality? Determinants of dropout behavior in developing countries. Journal of Human Capital, 2(1), 69-105.

[33] Hanushek, E. A., & Woessmann, L. (2010). The high cost of low educational performance: The long-run economic impact of improving PISA outcomes. OECD Publishing. 2, rue Andre Pascal, F-75775 Paris Cedex 16, France.

[34] Kane, T. J., Rockoff, J. E., & Staiger, D. O. (2008). What does certification tell us about teacher effectiveness? Evidence from New York City. Economics of Education review, 27(6), 615-631.

[35] Koedel, Cory (2008). Teacher quality and dropout outcomes in a large, urban school district. Journal of Urban Economics, 64 (3), 560-572.

[36] Konstantopoulos, Spyros (2007) : How long do teacher effects persist?, IZA Discussion Papers, No. 2893, Institute for the Study of Labor (IZA), Bonn.

[37] Lamb, S., & Markussen, E. (2011). School dropout and completion: An international perspective. In School dropout and completion (pp. 1-18). Springer, Dordrecht.

[38] Leigh, A. (2010). Estimating teacher effectiveness from two-year changes in students' test scores. Economics of Education Review, 29(3), 480-488.

[39] Logan, A. J. (2018). How Teachers Experience Change: A Case Study of the Merger Between Two Catholic Schools.

[40] Lucas Jr, R. E. (1988). On the mechanics of economic development. Journal of monetary economics, 22(1), 3-42.

[41] McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. Journal of econometrics, 142(2), 698-714.

[42] Miller, A. (2009). Principal turnover, student achievement and teacher retention. Princeton University: NJ.

[43] MIUR - Elenco Comuni di Montagna. https://archivio.pubblica.istruzione.it/reclutamento/allegati/elenco_comuni_montani_05.pdf.

[44] MIUR - Scuola in Chiaro. http://cercalatuascuola.istruzione.it/cercalatuascuola/

[45] MIUR - Elenco Scuole Piccole Isole. http://archivio.pubblica.istruzione.it:80/mobilita/bollettino/2010/scuole_isolane10.pdf.

[46] Mo, D., Yi, H., Zhang, L., Shi, Y., Rozelle, S., & Medina, A. (2012). Transfer paths and academic performance: The primary school merger program in China. International Journal of Educational Development, 32(3), 423-431.

[47] Oates, W. E. (1972). Fiscal federalism. Books.

[48] Rivkin, S. G., Hanushek, E. A., & Kain, J. F. (2005). Teachers, schools, and academic achievement. Econometrica, 73(2), 417-458.

[49] Romer, Paul (1990). Endogenous technological change. Journal of Political Economy 99, n.5, pt.II: S71-S102.

Appendix

Table 11: Density tests of the running variable

Sample	T-statistic	p-value	Obs
All schools	0.4913	0.6232	11400
LSS	1.7581	0.0787	6665
USS	1.3421	0.1796	4735

Source: Authors elaboration

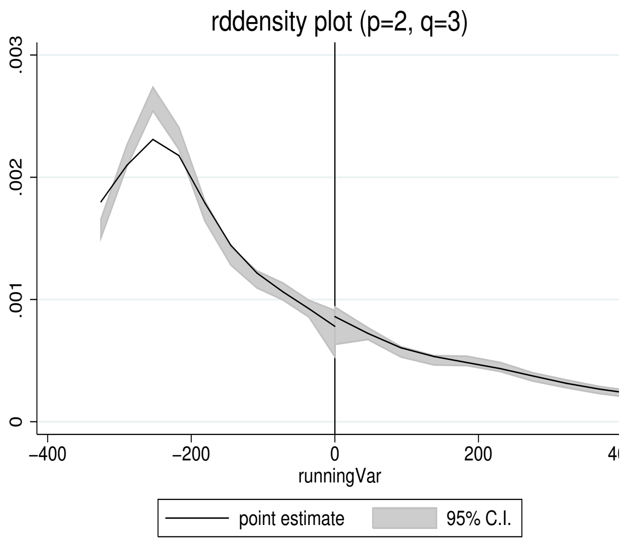

Figure 11: Estimated Density - All schools. Source: The authors

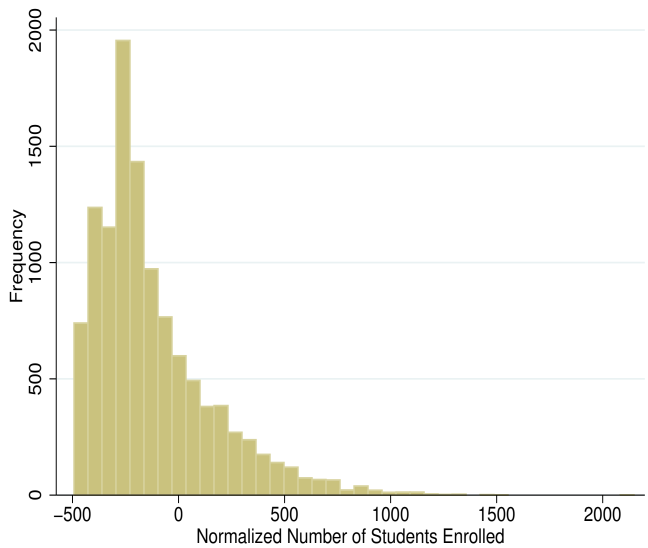

Figure 12: Histogram - All schools. Source: The authors

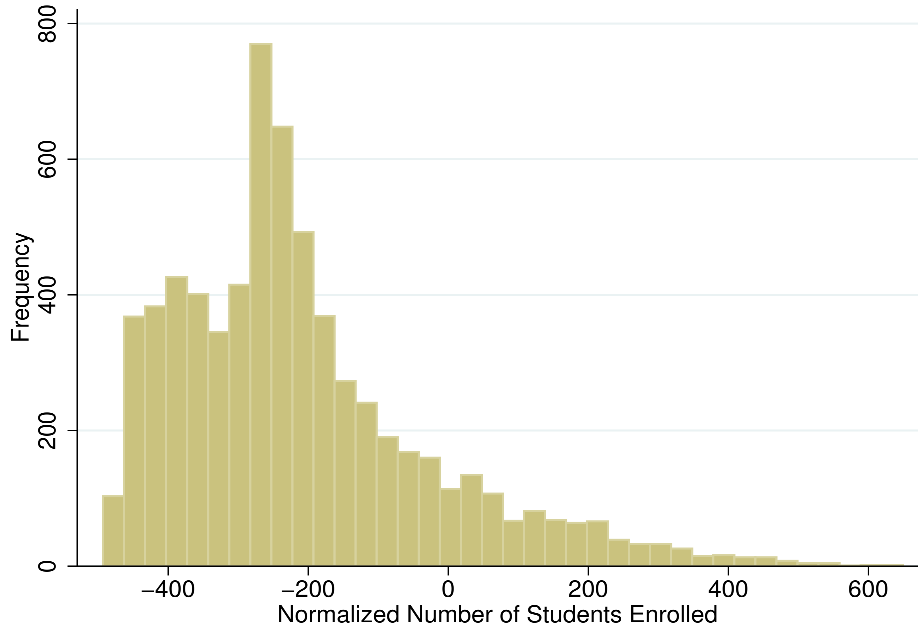

Figure 13: Histogram - LSS. Source: The authors

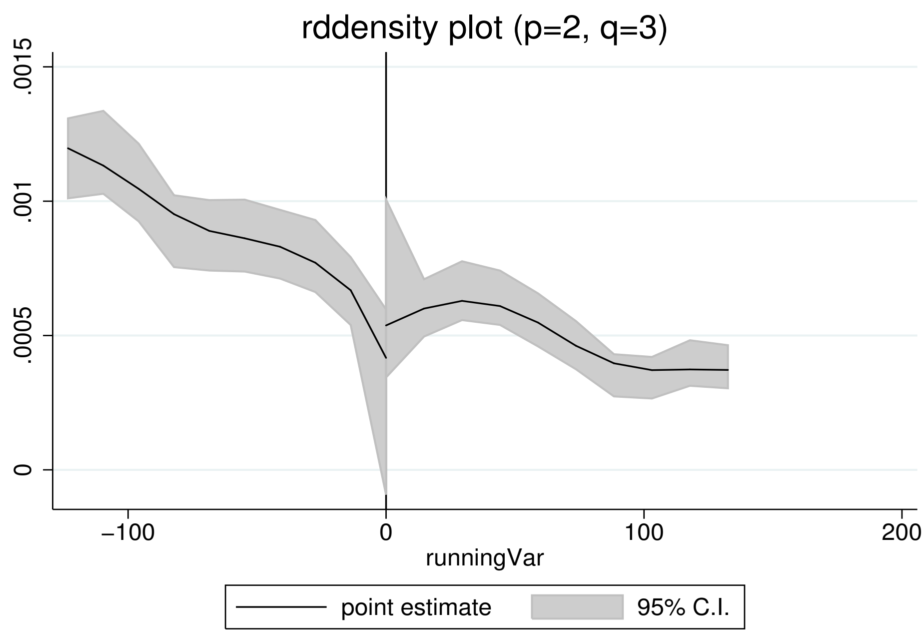

Figure 14: Estimated Density - LSS. Source: The authors

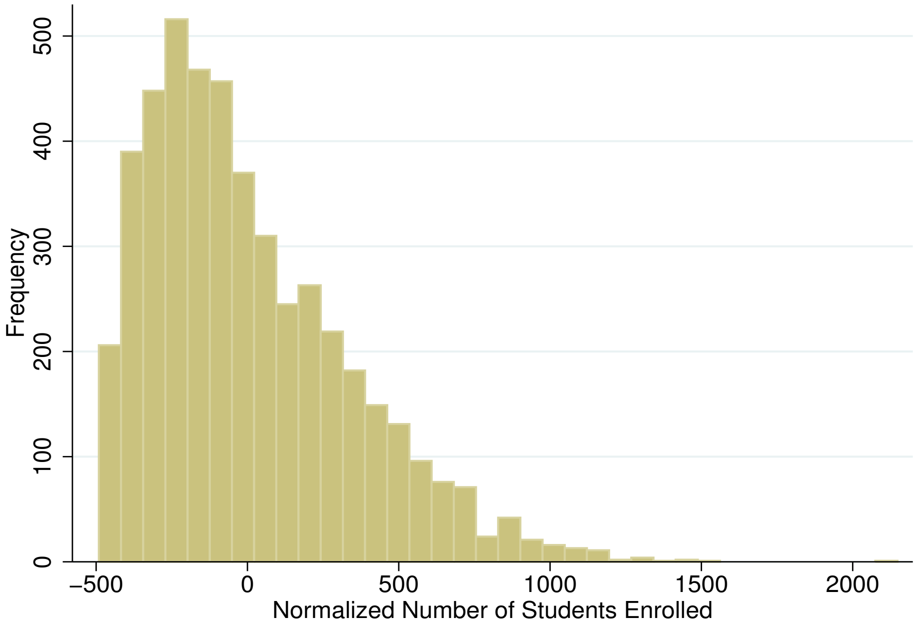

Figure 15: Histogram - USS. Source: The authors

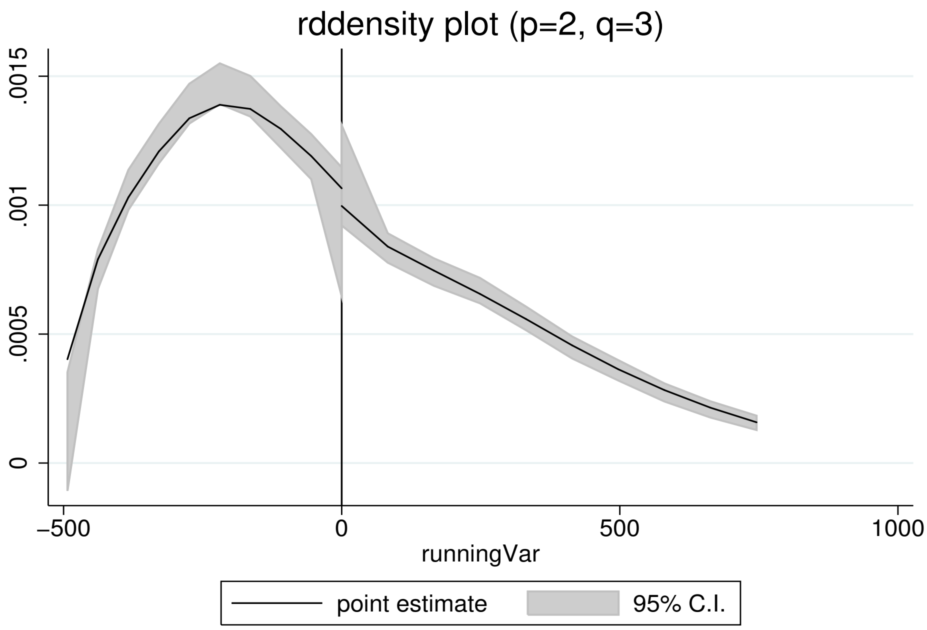

Figure 16: Estimated Density - USS. Source: The authors