The Effect of a Statewide School Voucher Program on School Enrollment Change Using Difference-in-Differences Methods

Hyun-Ki Shim
Florida State University

Abstract

This study examines the impact of the Florida Opportunity Scholarship Program (OSP), a school-based voucher program, on change in total enrollment and share of disadvantaged students by measuring the effect on timing of treatment: immediate effect, lagged effect, and cumulative effect. By collecting school- and district-level time-varying controls from the Census, Common Core of Data, and Florida Department of Education, this study constructed a panel dataset consisting of 1,945 Florida public elementary schools across 67 districts, spanning 2011 through 2016. In general, this study found a negative impact on total school enrollment change, but positive change on free-reduced lunch (FRL) share in enrollment. The negative effect of OSP was only significant within one more year when additional time indicators were included in the analysis. On the other hand, the FRL share shows no significant change from the immediate and lagged effects. All in all, OSP eligibility has a negative impact on total enrollment change which implies that underperforming schools experienced greater student displacement than other schools.

Keywords: School Choice Voucher, Florida Opportunity Scholarship, Under-Performing Schools, Difference-In-Differences, Enrollment Change

Introduction

The purpose of this study is to empirically gauge the effect of a school-based voucher program, the Florida Opportunity Scholarship Program (OSP), on enrollment change in underperforming schools (so-called "failing schools"). By using a difference-in-differences design, this study compared the change in total enrollment and disadvantaged students (i.e., free-reduced lunch [FRL]) as a share of failing schools to the same measures as their counterparts. Furthermore, this study anticipated a delayed effect of the program due to the practical challenges of students and families transferring and the time needed for awareness of eligibility and enrollment decisions by including lagged OSP indicators. This study also identified a persistence treatment effect associated with cumulative OSP eligibility: how the effect size changes as treatment is accumulated.

Among the various school choice policies that target different student subgroups and are supported by different financial sources, the OSP is unique because eligibility is equally distributed to all students within the school, as criteria are solely determined by the school grade based on school accountability. That is, unlike other types of school choice programs targeting certain disadvantaged students, such as disabled or low-income, all students within the failing school are eligible for OSP regardless of socioeconomic status (Florida Department of Education [FLDOE], 2018). More specifically, OSP provides an educational voucher to all students who are currently enrolled in or assigned next year to a low-performing school. The designation of a school as eligible for OSP is based on two school grade conditions: schools receiving (a) an F grade or (b) three consecutive grades of "D" from the school accountability system.

Originally, the program started in 1999 with the Florida A+ accountability system, which provided an option for students to transfer to either a higher-performing public or a private school. In 2006, however, the Florida Supreme Court declared that the option for a private school transfer was unconstitutional; since then, the only option for OSP-eligible students is transferring to other higher performing public schools within the state, with the district providing transportation. In addition, students who transfer to a higher-performing school cannot return to their initial school regardless of whether the school improves in subsequent years (Figlio & Page, 2003). These conditions may pose challenges for students and families who are making a decision about the quality of education. While families with higher levels of education and income are more likely to take advantage of the option to change schools upon receiving information about the benefits of various educational options, other families may need more support from the district in order to change schools and communities (Martinez, Godwin, Kemerer, & Perna, 1995).

In this context, pursuant to Florida Statutes section 1001.42(20) related to district policy regarding OSP, the program's success largely depends on district and school initiatives, as they encourage eligible students and families to participate in the program. For instance, the number of districts participating in OSP was very small—five among a total of 67 districts[1] in 2006 which increased to 33 districts in 2017. In terms of the number of participating schools, compared to 2006, the number of failing schools participating in OSP doubled by 2007 and multiplied about tenfold by 2011. The number of students using OSP also steadily increased from 1,315 to 4,424 by 2011 and then decreased to 3,074 by 2017 (see Figure 1). While the demand for the program is higher within primary school grades than secondary school grades (FLDOE, 2018)[2], the timing for the actual outcomes as students transferred was not immediately observed based on the trends in a number of schools and students.

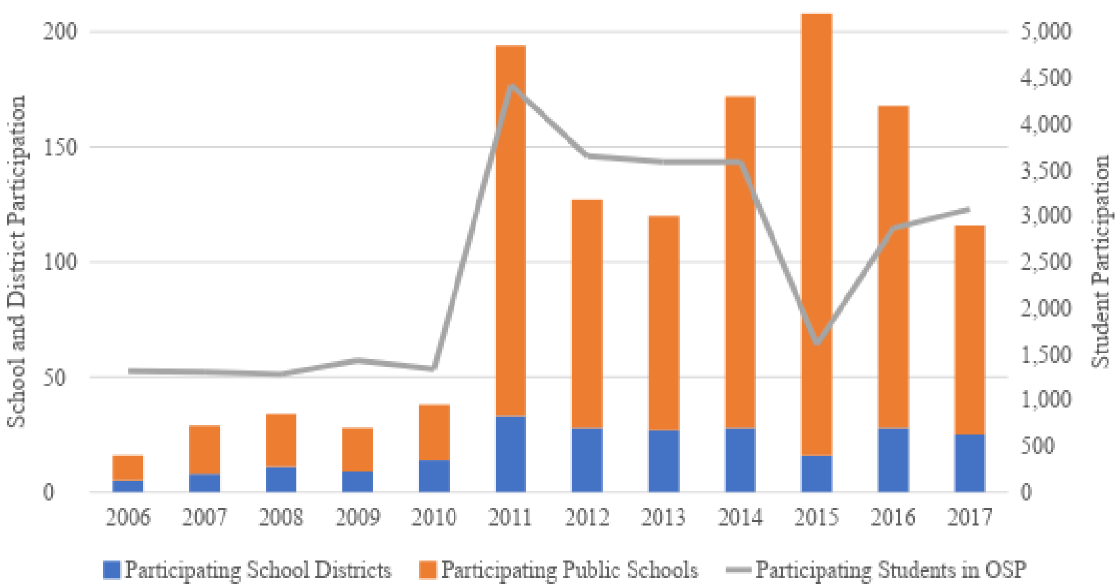

Figure 1*. Trends of OSP Participation: Student, School, and District*

[1] Excluded seven of the total of 74 districts: four research and three specialized schools (special education and juvenile delinquency).
[2] Retrieved from http://www.fldoe.org/schools/school-choice/k-12-scholarship-programs/osp/

Theoretically, the underlying motivation behind school choice that affects overall enrollment and student composition is the demand for quality education (Hoxby, 2003). Generally, students' mobility for a better-quality education leads to enrollment changes in schools and districts (Pane et al., 2008), and this is often found in Tiebout choice theory (1956). For instance, failing schools, where disproportionately disadvantaged students are enrolled, may experience a greater change in their student composition than other schools (Figilo & Page, 2003). A typical example of the school-choice effect is “cream-skimming,” where high-performing students leave traditional public schools by using the school choice program in a low-income district (Altonji, 2015; Walsh, 2009). In addition to students' academic abilities, socioeconomic status and demographic factors are also associated with demand for school choice. For example, Clotfelter (1999) identified “white flight”, indicating the loss of white students in urban school districts as their families move to suburban areas due to race and economic considerations. This means that schools and districts with a high proportion of low-income families are more likely to face a threat from the educational voucher choice program by losing not just overall students but advantaged students (Egalite, 2013). As a result, this study suggests that a school designated as “failing” under OSP will more likely experience enrollment change afterwards whether the free-reduced lunch students use the educational voucher opportunity to transfer to higher-performing schools or not.

Thus, this study focuses on three main points in order to estimate the average effect of OSP on the change in total enrollment and FRL share: (a) how a school experiences change in total enrollment and FRL share by OSP eligibility, (b) whether the effect, if any, was delayed if students decided to transfer later, and (c) how cumulative OSP eligibility is associated with enrollment change in failing schools.

Based on the strict requirements and clear guidelines of the OSP policy, a parsimonious approach was employed that aims to investigate the immediate, lagged, and cumulative effect of OSP on change in school enrollment. The specific and rigorous standard of OSP, based on school accountability, provides a clear difference between treatment and control groups each year. While a school could be eligible for OSP many times in accordance with the school accountability system, school-based eligibility is limited to only those students who are enrolled or assigned in the specific year when a school is designated as failing. Given that both the racial or ethnic identity of students as well as poverty are tightly linked to enrollment patterns (Ryan & Heise, 2002) and the most disadvantaged public-school students are clustered in low-income districts (Chaplin, 2001), this study provides a better understanding of how an equal opportunity has been used within a school by tracking total student enrollment change under a school-based voucher program.

In sum, the overarching question of this study is whether OSP school voucher eligibility affects the change in total enrollment and FRL share in failing schools. Additionally, an important question is whether there is a persistent lagged effect and cumulative effect of OSP. The results of this study will have valuable implications for policymakers and program practitioners. Particularly for the lagged and cumulative effects, these issues could provide insight into how school choice can effectively pressure enrollment change from a long-term perspective. Thus, the specific research questions for this study are:

1. What is the effect of Opportunity Scholarship Program (OSP) on change in overall enrollment and the share of FRL students in failing schools across districts?
2. How do the effects of OSP persist in the change of overall enrollment and the share of FRL students even after the program's introduction?
3. Does the effect, if any, vary by cumulative OSP eligibility?

Background and Literature Review

Florida Opportunity Scholarship Program

In 1999, Florida introduced the Opportunity Scholarship Program, which is a unique statewide school choice program with an accountability system that is similar to the federal No Child Left Behind program (Chakrabarti, 2010). The program utilizes vouchers, giving students from low-performing public schools the option to transfer to higher-performing public schools. Through the program, all enrolled public-school students are eligible to receive a voucher if the school is designated as “failing.” These OSP-eligible schools are determined based on two school grade conditions: schools receiving (a) an F grade or (b) three consecutive grades of “D” from the school accountability system. Thus, OSP-eligible schools are often stigmatized due to their poor mark (Chakrabarti & Schwartz, 2013).

Originally, the implementation of grades for accountability were based on student performance on the Florida Comprehensive Assessment Test (FCAT). The letter grades, on a scale of A through F, converted from a five- or six-point scale, were assigned to schools beginning in 1999. If a school failed to meet the minimum criteria in all subjects of the FCAT, the school received an F grade. If a school failed to achieve the minimum criteria in at least one subject area, the school earned a D grade. In order to receive a C grade, a school had to meet the minimum criteria in reading, writing, and mathematics (Figlio & Page, 2013). To qualify for a C grade, a school was required to have at least 60 percent of its test-takers achieve level 2 or above in both reading and mathematics, as well as 50 percent of its test-takers achieve level 3 or above in writing (Chakrabarti & Schwartz, 2013).

School-Based Vouchers and School Enrollment

The enrollment changes in schools under the school choice program imply a demand for quality education (Hoxby, 2003). The quality of education is an important determinant of voucher utilization from an individual perspective, and this can be seen through changes in public school enrollment. Generally, the displacement of students for higher quality education leads to a change in student composition at a school (Pane et al., 2008) and is often found in Tiebout choice theory (1956).

First, student demographics, such as race and ethnicity, are significantly related to demand in school choice programs. For instance, Clotfelter (2004) identified “white flight,” indicating white families move to suburban regions causing loss of white students from economically advantaged families and lower urban district enrollment. Recent studies have found that the racial and ethnic identity of students and poverty are tightly linked in school enrollment patterns; racial and economic segregation, however, tends to occur between districts rather than within districts (Ryan & Heise, 2002).

Furthermore, a report on racial integration in schools revealed that the most disadvantaged public-school students are clustered in poorer districts (Chaplin, 2001). That is, students’ educational needs related to socioeconomic status, such as poverty, disability, and language learning, have been significantly related to enrollment change (U.S. Government Accountability Office, 2016). Families with the financial means to do so tend to opt out of urban school districts or send their children to local private schools (Posey, 2012). Across districts in the United States, English language learners (ELL) are among the fastest-growing student groups in the public education system, reflecting increased immigration to the United States (National Clearinghouse for English Language Acquisition, 2010)[3]. The continuous growth of this population has been a concern for public schools in terms of meeting certain standards of education quality. Another important educational need that affects school enrollment is student disability. Families of students with

[3] Retrieved from http://nces.ed.gov/ccd/rural_locales.asp.

disabilities have different preferences and decisions to make regarding school choice compared to non-disabled students (Cullen & Rivkin, 2003).

Therefore, these student as well as district background factors, such as race/ethnicity and educational needs, are important in understanding the trends of school enrollment changes under a school choice program. Explaining how student composition shifts in accordance with a school-based voucher choice program is an important factor in the analysis of school-level enrollment.

Summary

The rationale of this study deviates from previous research about educational inequality focusing on the stratification of student race, achievement, socioeconomic status, and religion. Most research in this area has examined the impact of school choice on racial segregation (Egalite & Wolf, 2016; Garcia, 2008). However, less research has focused on actual school choice demand as it pertains to student economic backgrounds when school choice opportunity is offered to all students evenly (Owens, 2018). For instance, past research on racial and economic segregation distinguished between students from low and high income families assuming unequal choice options based on economic backgrounds (Quillian, 2014; Vigdor & Ludwig, 2008). Unlike previous research comparing the program effects under unequal choice options, this study examines the average effect on overall students and low-income students as defined by FRL under equal choice options.

In this context, I argue that, for various reasons, students from low socioeconomic families are less likely to participate in the school choice program despite equal opportunity to do so. Focusing on the school-based voucher program using school panel data, this study offers meaningful results on how school choice programs actually changed the socioeconomic composition of schools.

Methods

This section discusses the quasi-experimental research design that was selected to identify the effects of OSP on total and FRL student enrollment. Specifically, I will first discuss the concern about selection bias in the sample, which is not uncommon in an accountability system. Moreover, I will explain the analytic strategy that is appropriate for this study after testing a parallel trend assumption. Lastly, I will present the data and variables included in our analysis as well as a descriptive portrait.

Strategically, this study uses a difference-in-differences (DID) approach to estimate the immediate, lagged, and cumulative effects of the program with different specifications. The basic DID model estimates the effect of the program by comparing the differences in outcomes of failing schools to the same measures in non-failing schools before and after the intervention. Thus, this study considers enrollment change the year before the program introduction as a baseline and the difference in enrollment patterns after a school receives OSP as the treatment effect. Then, this study further differentiates the effect of OSP separately into lagged or delayed effects in the timeline and accumulated by eligibility.

For research question 1, this study uses a preliminary analysis of DID, given that OSP eligibility is restricted to one year and possibly to eligible subsequent years. Purposely, I attempt to capture the immediate effect of OSP on average change in outcomes. This model is often interpreted in the same way as the DID approach, with multiple groups across multiple years, so this equation focused on a parsimonious and mathematically equivalent form (Dealaney & Hamenway, 2017). Specific estimation follows the regression model equation (1):

$$(1)\qquad Y_{sdt} = \beta_0 + \beta_1(OSP_{sdt}) + \theta(X_{sdt}) + \lambda_t + \delta_s + \varepsilon_{sdt}$$

where Y_{sdt} represents the outcomes of interest (i.e., change in total enrollment and FRL share) corresponding to school s and district d in time t. This equation (1) includes the policy intervention, OSP, as a treatment in a binary variable equaling 1 if school s in district d is eligible for OSP in time t. Considering that the treatment effect will show next year's enrollment, the OSP indicator already includes a one-year lag in the first specification. β_1 indicates the change in the overall level of enrollment due to OSP, controlling for how much the measures in the schools without treatment deviate from their specific time trend in the same years. X is a vector of time-varying school- and district-level controls that may affect outcomes. These school control variables include the percentage of male students, white or black student subgroups, FRL, disability, non-English language learners, and school grades. District-level controls include percentage of white or black students, population aged 5–17, percentage of residents with a graduate degree, unemployment rate, and median household income. λ is the year fixed effect; and δ is the school fixed effect.

While the OSP did not immediately lead to a critical change in schools, the trends of school and student participation in OSP are somewhat gradual after 2012 as evidenced by delayed participation. For research question 2, therefore, this study further investigates the relationship between delayed participation and enrollment change by including a series of lagged indicators in addition to the OSP indicator, which already lagged by one year as follows (2):

(2) $$Y_{sdt} = \beta_0 + \beta_1(OSP_{sdt}) + \beta_2(OSP_{sdt+1}) + \beta_3(OSP_{sdt+2}) + \beta_3(OSP_{sdt+3}) + \theta(X_{sdt}) + \lambda_{st} + \delta_s + \varepsilon_{sdt}$$

As shown in equation (2), this study further takes into account two-, three-, and four-year lags. For instance, a school designated as "failing" under OSP in 2011 had the base year 2012 as its *OSP* indicator and additional indicators for 2013, 2014, and 2015. Under this specification, this study attempts to reflect the increasing demand of students in OSP on the assumption that many students may not make a decision as soon as they are eligible to do so. That is, I will test how long the OSP eligibility takes to be observed as eligible students transfer to higher-performing schools.

Lastly, for research question 3, this study identifies the cumulative effect of OSP eligibility. As Table 4 shows school differences by cumulative eligibility, I intuitively employ a general DID identification strategy to calculate the cumulative effect of OSP eligibility. This approach provides a better sense of the growth and threshold of treatment dosage on outcome distinguishable from the immediate effect of the program. The specification for research question 3 is as follows (3):

(3) $$Y_{sdt} = \beta_0 + \beta_1(First_{sdt}) + \beta_2(Second_{sdt}) + \beta_3(Third_{sdt}) + \beta_1(Fourth_{sdt}) + \beta_2(Fifth_{sdt}) + \beta_3(Sixth_{sdt}) + \theta(X_{sdt}) + \lambda_{st} + \delta_s + \varepsilon_{sdt}$$

where each cumulative eligibility is a binary variable (whether the school *s* in district *d* in time *t* is designated as "failing" within the analytic window from 2011 to 2016). Considering the limited analytic window, the cumulative OSP eligibility ranges from 1 to 6, indicated as *First* to *Sixth* in the specification. For instance, school *s* in district *d* has a value that equals 1 for variable *First* in the year *t* when it is first eligible for OSP. Moreover, when eligible for the second time, *Second* equals 1 in that year *t*. As noted above, this general model of DID with multiple treatment groups across multiple years is interpreted by the OSP indicator as an original interaction term in the standard DID model (Clair & Cook, 2015).

Next, I will present the data sources and variables used for this study, as well as illustrate a portrait of failing schools and their trends with respect to the dependent variables.

Data Sources and Variables

This study attempts to model the effects of a school-based voucher, OSP, on enrollment change. In order to estimate the year-to-year enrollment change at a school, I used school-level panel data consisting of school and district characteristics that influence student enrollment. Excluding vocational, special, and other schools as well as secondary schools, a total of 1,945 traditional public elementary schools across 67 school districts were included in the analysis. Since the treatment effect is based upon the school level, all standard errors are clustered at the district level. In addition, the results of the models are consistent with the initial basic Model 1, including school controls in Model 2 and district controls in Model 3.

The primary data source for this study is imported from the Florida Department of Education (FLDOE), which maintains a rich set of longitudinal databases containing a variety of Florida public school and district characteristics. This study uses school-level panel data spanning the years 2011 through 2016, comprising school and district characteristics that influence student enrollment under the school choice program. Specifically, the time-variant observable factors and time-invariant unobservable factors, such as demographic and socioeconomic characteristics, are included in the school- and district-level controls. Detailed data sources and variables are described in Table 1.

Policy treatment in the analysis refers to schools eligible for OSP and designated as “failing” based on a school grade report. Those indications of OSP-eligible schools and school grades are

Table 1. *Description of Data and Variables*

Name	Description	Sources
Dependent variables		
Change of total enrollment	%	NCES Common Core Data
Change of free reduced lunch share	%	NCES Common Core Data
Treatment: Opportunity Scholarship Program		
Eligibility (designated as “failing school”)	0/1	FL DOE OSP
Cumulated OSP eligibility	0~6	Calculated
School-level control variables		
Male student	%	FSIR
White student	%	FSIR
Black student	%	FSIR
Free or reduced priced lunch	%	FSIR
Student with disability	%	FSIR
Non-English language learner	%	FSIR
School grades	Category of A–F	FSIR
District-level control variables		
White population	%	Census ACS
Black population	%	Census ACS
Population of age 5–17	%	Census ACS
Degree over BA	%	Census ACS
Unemployment rate	%	Census ACS
Median household income	Logged and CPI	Census ACS

Note. FSIR = Florida School Indicator Report; ACS = American Community Survey. Additional information about OSP is available at http://www.fldoe.org/schools/school-choice/k-12-scholarship-programs/osp/

imported from the OSP annual report and Florida School Indicators Report (FSIR), respectively. Including our main outcome of interest, change in total enrollment and FRL share, most school-level data were drawn from the FSIR: percentage of students receiving FRL, percentage with limited English proficiency, percentage of students with disabilities, and race/ethnicity. District-level data were imported from The Common Core of Data maintained by the National Center for Educational Statistics and the U.S. Census Bureau's American Community Survey: district demographics (e.g., percentage of population aged 5–17, race/ethnicity), district educational and economic characteristics (e.g., percentage of residents with a graduate degree, unemployment rate, and median household income). Financial data were log transformed after adjusted in 2016 dollars using the Consumer Price Index (CPI) value. Complete descriptive statistics for all variables in the analysis are provided separately in Table 2 by year and group and in Table 3 by group and cumulative eligibility.

Table 2. *Descriptive Statistics of Outcomes (Total Enrollment & FRL Share) by Year*

Year	Group	Total Enrollment (Mean)	FRL Share (%)	Change in Total Enrollment (%)	Change in FRL Share (%)	*N* of Schools
2011	Control	645.1	63.9	1.9	1.5	1,922
		(258.1)	(24.6)	(22.2)	(5.3)	
	Treatment	514.5	90.8	-7.2	2.4	23
		(224.0)	(7.6)	(11.2)	(3.7)	
2012	Control	645.3	64.5	0.9	0.7	1,913
		(254.8)	(24.8)	(14.9)	(5.2)	
	Treatment	499.2	89.8	-3.4	-1.0	32
		(227.2)	(12.7)	(13.3)	(6.7)	
2013	Control	652.0	60.9	1.8	-3.3	1,892
		(258.0)	(25.4)	(13.3)	(16.8)	
	Treatment	557.3	80.6	-4.7	-10.4	53
		(209.7)	(24.2)	(9.2)	(24.1)	
2014	Control	658.7	60.6	1.2	0.2	1,848
		(265.7)	(26.1)	(8.7)	(14.4)	
	Treatment	564.3	80.6	-3.0	0.8	97
		(184.4)	(18.3)	(7.9)	(11.3)	
2015	Control	664.4	63.1	0.7	3.0	1,798
		(267.4)	(24.2)	(15.9)	(16.5)	
	Treatment	539.9	89.2	1.0	5.4	147
		(184.9)	(10.6)	(12.9)	(17.5)	
2016	Control	660.2	61.6	0.7	-2.2	1,849
		(267.7)	(25.2)	(8.25)	(15.9)	
	Treatment	572.4	86.4	-5.6	-1.2	96
		(196.7)	(8.8)	(10.8)	(3.6)	

Note: Control group: Non-OSP eligible school. Treatment group: OSP eligible school. Standard deviation in parentheses. All values are rounded to nearest 1/10 for efficient communication and space purposes.

Table 3. *Descriptive Statistics by Cumulative OSP Eligibility (Analytic Window: 2011–2016)*

	All	Non-OSP	OSP	(Frequency)					
	Avg.	Avg.	Avg.	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable									
Membership	650.1	658.0	539.2	534.7	540.9	557.2	571.1	513.0	623.0
	(260.5)	(262.3)	(202.5)	(202.5)	(208.8)	(213.4)	(165.4)	(121.3)	(48.1)
School									
Male students (%)	51.7	51.7	52.1	51.0	52.4	52.2	52.0	52.0	50.5
	(3.4)	(3.4)	(2.6)	(2.7)	(2.5)	(2.6)	(2.0)	(3.2)	(3.0)
White students (%)	40.2	41.4	19.4	20.0	18.3	17.0	17.0	25.0	37.8
	(26.8)	(26.7)	(18.5)	(18.7)	(17.4)	(17.5)	(17.5)	(26.1)	(50.6)
Hispanic students (%)	30.2	30.4	26.4	27.4	25.8	23.7	24.2	7.7	12.1
	(25.1)	(25.2)	(22.7)	(22.6)	(22.8)	(22.9)	(26.4)	(4.2)	(6.5)
Black students (%)	26.4	24.3	55.1	53.9	55.2	60.8	60.6	69.4	45.8
	(26.2)	(24.7)	(29.1)	(29.0)	(29.0)	(28.6)	(31.5)	(30.0)	(60.5)
FRL students (%)	63.3	61.8	85.0	85.0	84.8	84.6	89.8	86.2	91.4
	(25.2)	(25.1)	(15.7)	(16.3)	(15.0)	(16.0)	(9.1)	(7.2)	(9.0)
Non-ELL (%)	86.6	86.8	84.0	83.4	84.9	84.1	85.2	96.4	96.6
	(14.2)	(14.1)	(15.2)	(15.4)	(14.4)	(16.1)	(14.7)	(3.1)	(0.6)
Disabled (%)	14.2	14.2	14.6	14.4	15.0	15.3	16.0	14.0	13.4
	(8.7)	(8.9)	(5.3)	(5.4)	(5.3)	(4.6)	(3.7)	(3.5)	(2.1)
District									
White (%)	77.0	77.2	75.0	74.8	76.0	74.3	76.3	73.0	82.2
	(8.9)	(8.8)	(9.5)	(9.4)	(9.4)	(10.3)	(10.7)	(10.0)	(12.1)
Black (%)	17.1	17.0	19.3	19.4	18.6	20.2	18.4	20.6	12.2
	(7.8)	(7.7)	(8.7)	(8.6)	(8.2)	(10.1)	(9.8)	(8.7)	(8.5)
Population age 5–17 (%)	15.2	15.2	15.0	1519	14.9	14.7	14.5	15.2	15.9
	(1.7)	(1.7)	(1.4)	(1.3)	(1.6)	(1.4)	(1.5)	(1.8)	(1.1)
Degree over BA (%)	0.36	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Unemployment rate (%)	10.5	10.5	9.8	10.0	9.5	9.5	8.9	8.6	8.1
	(1.8)	(1.8)	(1.6)	(1.5)	(1.4)	(1.7)	(1.4)	(1.0)	(0.2)
Median income (ln)	10.8	10.8	10.8	10.8	10.8	10.8	10.8	10.8	10.8
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)	(0.2)	(0.0)	(0.1)
Number of schools	11,670	10,894	776	512	162	65	27	8	2

Note. Standard deviation in parentheses. All values are rounded to nearest 1/10 for efficient communication and space purposes.

Descriptive Statistics

One limitation in evaluating the effect of OSP on enrollment change is that the program assignment is non-random, so OSP-eligible schools may differ from other schools in characteristics that affect both eligibility and outcomes. Although the DID model allows for group differences in level of outcomes in the pre-treatment period, problems arise when their trends over time differ without the treatment. However, the parallel trend assumption allows us to estimate the policy's effects without violating selection bias. Although there is no clear guideline for testing these assumptions, this study explored this issue both descriptively and graphically.

Table 2 shows the descriptive statistics of the outcomes of interest by year between groups. Annual means are accurately estimated, and year-to-year volatility is relatively low, so it is easy to spot deviation from the parallel trend assumption in a long time-series (Wing et al., 2018). As no exceptional value is observed in each year, we can assume that no shock other than OSP eligibility occurred during the analytic window (2011–2016), nor did any event occur within the window that should have affected both groups equally (Dimick & Ryan, 2014). In other words, there were no noticeable numbers in each year corresponding to a different event or shock other than OSP. The absence of contemporaneous shock ensures that other events occurring at the same time or after the treatment effect will have the same effects on the treatment and control groups.

This study further illustrates the parallel trends of outcome of interest (*Y*), change in total enrollment, and FRL share between the treatment and control groups in Figure 2 (i.e., the trajectory of an outcome (*Y*) at three points in time, $t = 1$ and $t = 2$, before and after the event for the treatment and control groups). For the main outcome, total enrollment changes show a clear parallel pathway between the groups in the pre-treatment periods. This implies that our outcomes of interests are changing at the same rate in the pre-periods for both the treatment and control groups. Moreover, any variability in the differences between groups is attributed to the program effect, not differential pre-existing trends (Ryan et al., 2015). Similarly, the trajectory of share of FRL enrollment between groups also showed clear common trends in Figure 2. The trajectory between control and treatment groups is nearly parallel before the treatment period.

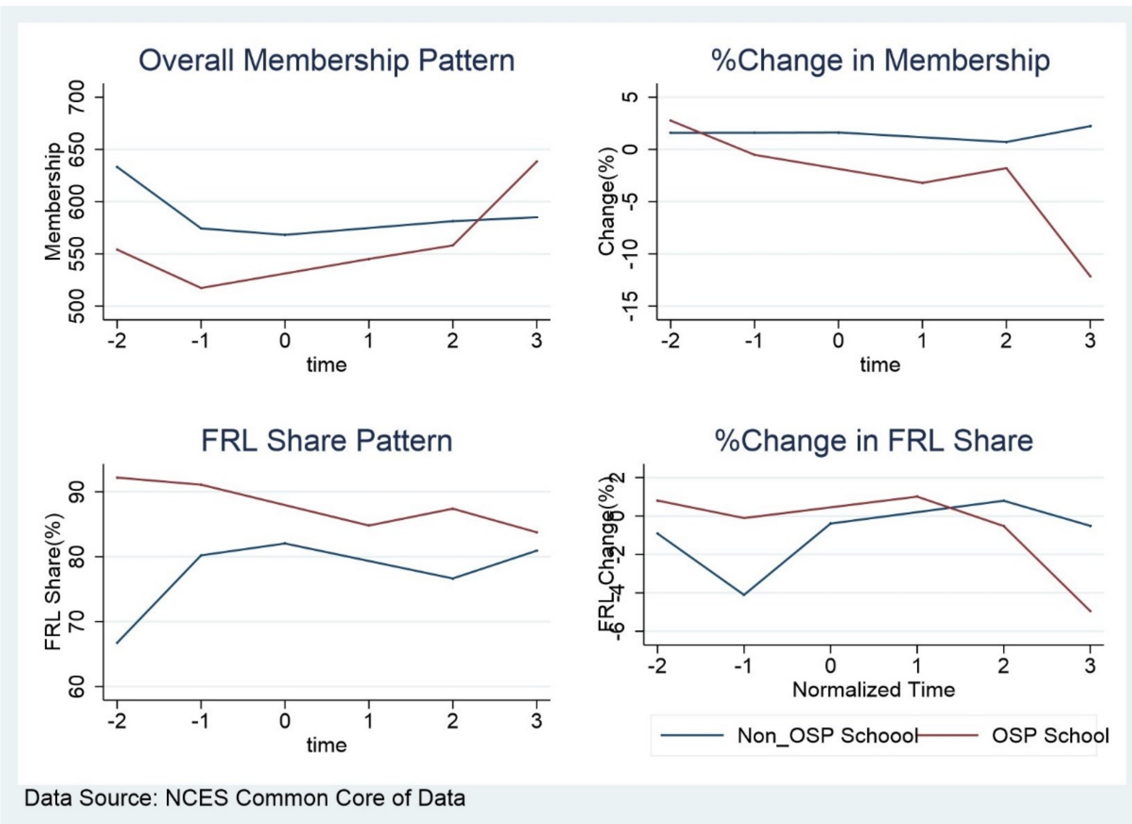

Figure 2. *Enrollment Pattern Before and After the OSP: Analytic Window 2011–2016*

Table 3 shows the average statistics of the control and treatment groups, as well as cumulative OSP eligibility within the analytic window. A clear difference in the level of school characteristics between treatment and control groups, except for the percentage of male and disabled students, was demonstrated. Moreover, as OSP eligibility accumulates, the difference exhibits a clear pattern among groups. From these tables and graphs, an explicitly clear difference is evident in level outcomes and parallel pre-treatment period trends between OSP and non-OSP schools for total enrollment change. Thus, it is tenable that the intervention altered the trajectory of the targeted group.

Results

Tables 4 and 5 present the results from the first two DID analyses for estimated OSP effects on enrollment change using a panel dataset. For both tables, regression models were run, adding school controls (Model 2) and district controls (Model 3) to the basic Model 1, which included only a single post-OSP indicator. Moreover, the last Model 5 included the additional lags from the initial OSP indicator. Additionally, the first panel (A) labeled "OSP" indicates the effect of the program on the change in overall enrollment and FRL student share. That is, OSP equals 1 for school *s* in district *d* in year *t* if it was designated as a "failing" school under OSP.

For research question 1, schools designated as "failing" under OSP are shown to have significant effects on the overall enrollment change. Specifically, in Table 4, OSP attributes an estimated drop in overall enrollment change between 4.0% (Model 3) and 5.3% (Model 5). In addition, the significantly negative effect of OSP on the change in total enrollment is greater with the additional lags (Model 4). Given that the OSP effect was significantly stronger in the first and second years than afterwards, it can be assumed that the students and families are not hesitating to decide on the school transfer under the choice option. Still, Table 5 shows that this study found no significant effect of OSP on a change in the enrollment of FRL-eligible students. All base

Table 4. *Average Effect of OSP on the Change of Total Enrollment*

	Model 1 Basic	Model 2 School Control	Model 3 District Control	Model 4 Additional Lags
OSP	-4.61***	-4.06***	-4.06***	-5.35***
	(0.68)	(0.77)	(0.78)	(1.36)
Additional lags				
OSP (n + 1yr)				-2.48*
				(1.10)
OSP (n + 2yr)				-0.30
				(1.13)
OSP (n + 3yr)				-1.84
				(1.18)
District-fixed	No	No	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes
Cluster *S.E.*	-	District	District	District
Number of schools	11,669	10,264	10,264	4,741
R^2	0.006	0.026	0.026	0.027

Note. Robust *S.E.* are in parentheses. Table 4A in the Appendix shows complete results including full school-district covariates. Estimated coefficients are rounded to nearest 1/100.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5. *Average Effect of OSP on the Change of the FRL Enrollment Share*

	Model 1 Basic	Model 2 School Control	Model 3 District Control	Model 4 Additional Lags
OSP	1.11	2.35	2.31	0.84
	(0.68)	(1.45)	(1.46)	(2.41)
Additional lags				
OSP (n + 1yr)				0.29
				(2.17)
OSP (n + 2yr)				-1.27
				(2.26)
OSP (n + 3yr)				-1.74
				(1.64)
District-fixed	No	No	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes
Cluster *S.E.*	-	District	District	District
Number of schools	11,648	10,261	10,261	4,738
R^2	0.029	0.039	0.04	0.049

Note. Robust *S.E.* are in parentheses. Table 5A in the Appendix shows complete results including full school-district covariates. Estimated coefficients are rounded to nearest 1/100.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

years for FRL enrollment change have no negative coefficient. Considering that the additional lags also have no relationship with a change in FRL enrollment, one possible explanation is that FRL students and their families are not affected by OSP even though they have a definite need for quality education. These results are consistent with the descriptive results in Table 3 that schools receiving more OSP eligibility had a larger share of FRL students in their overall enrollment. Combining Tables 4 and 5, this study found a significantly negative effect of OSP on overall enrollment change not only in the base year when the school was designated as “failing” but also the following year (Table 4, Model 5). At the same time, the results for the change in share of FRL student enrollment show no significant relationship even when additional lags were included (Table 5, Model 5).

In addition to identifying the immediate and lagged effects of OSP on total enrollment change, this study further examines the cumulative effect by incorporating eligibility frequency which may lead to a greater change in enrollment. In Table 6, regarding research question 3, a model is estimated with categorical variables consisting of cumulative OSP eligibility from 1 to 6 in a given analytic window, 2011–2016. The results show some evidence of linearity in the cumulative effect of OSP eligibility on total enrollment change, but not on FRL share.

The first column of Table 6 reports statistically significant findings in the relationship between total enrollment change and the cumulative effect. Specifically, the cumulative OSP effect showed an average decrease of 4.44% in first-time eligibility, 4.51% in second-time eligibility, and 3.04% in third-time eligibility. The effect size appears to be decreasing and stagnates as treatment accumulates. Interestingly, the pattern of effect size showed a decline by fourth-time eligibility, but fifth-time eligibility showed a significant 16.2% decrease in OSP schools. On the other hand, as shown in the second column of Table 6, the cumulative effect is not linked to the change in FRL share. The only significant effect found was in fourth-time eligibility, about a 5.58% increase. This finding may be due to the fact that a change in FRL share is related to a change in total enrollment, so that it appeared to be significant after a discernable change occurred in total enrollment, except for disadvantaged students.

Table 6*. Average Effect of Cumulative OSP Eligibility on the Enrollment Change (Analytic Window: 2011–2016)*

	Total Enrollment	FRL Share
OSP Cumulated Eligibility (0/1)		
First	-4.44***	3.21
	(1.10)	(1.84)
Second	-4.51***	2.36
	(0.98)	(2.11)
Third	-3.04*	-1.32
	(1.16)	(3.42)
Fourth	-2.21	5.58**
	(3.65)	(1.98)
Fifth	-16.20**	5.16
	(5.72)	(3.12)
Sixth	-5.95*	7.84
	(2.79)	(4.32)
Includes school and district control	Yes	Yes
District-year fixed	Yes	Yes
Number of schools	10,264	10,261
R^2	0.023	0.041

Note. Robust *S.E.* in parentheses. Table 6A in the Appendix shows results including full school-district covariates. Estimated coefficients are rounded to nearest 1/100.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

All in all, this study finds a negative effect on total school enrollment change, as seen in Figure 3-1, which shows that a pre-treatment pattern lies around zero but becomes negative in the treatment period. On the other hand, in Figure 3-2, the FRL share of total enrollment is positively associated with the OSP effect, which implies that OSP-eligible schools have experienced a greater increase of FRL students due to the treatment effect.

Conclusions

The findings of this study suggest that statewide school-based voucher programs affect overall student enrollment, but not the share of FRL students in under-performing schools. Overall enrollment in under-performing schools significantly decreased after the OSP intervention. The magnitude of impact increased as the eligibility accumulated; however, the share of disadvantaged students, such as FRL, was not affected. These results are in line with previous studies focusing on who benefits from school choice (Campbell, West, & Peterson, 2005; Cato Institute, 2018). Specifically, the Florida school-based voucher program increased the segregation of students by socioeconomic status, with FRL students remaining in under-performing schools. One possible explanation is that economically advantaged and high achieving students have families that tend to enroll their children in high-performing schools, while disadvantaged students remain in their default neighborhood school.

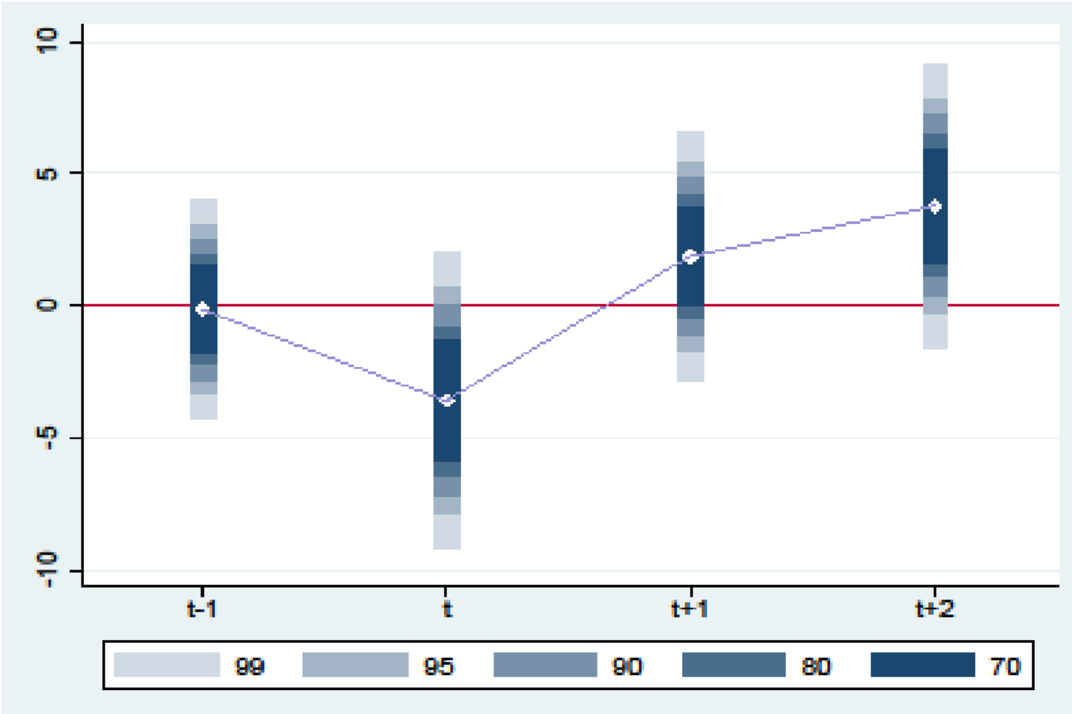

Figure 3-1. *Parallel Trend Assumption Test Using Lags and Leads: Change in Total Enrollment*

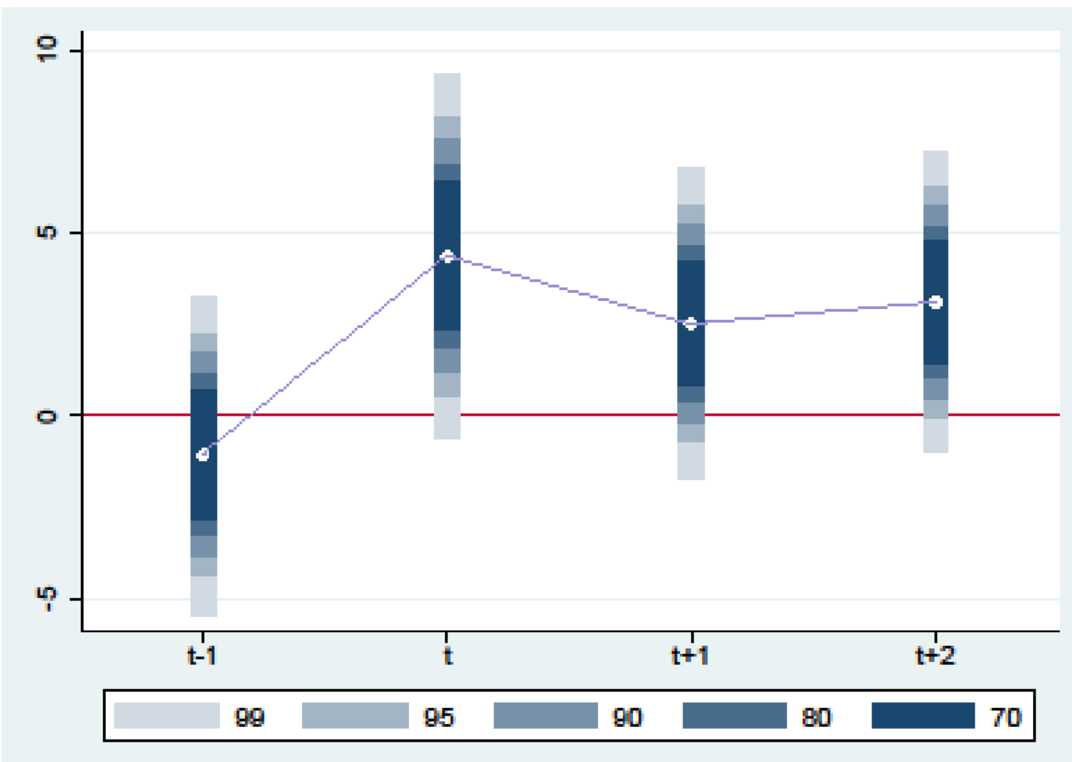

Figure 3-2. *Parallel Trend Assumption Test Using Lags and Leads: Change in FRL Share*

More clearly, this study can conclude a simple and straightforward point from the findings. First, students' access to school choice is directly and powerfully related to their socioeconomic status. In terms of the source of this inequality, socioeconomic status is a stronger factor than race as far as the student achievement and attainment gap (Bell, 2009). Also, it means that economic stratification is a key pathway for peer effects. Parents' preferences for economically homogenous schools and school districts have been shown in previous research (Owens, 2018; Owens, Reardon, & Jencks, 2016). These studies explored economic stratification trends within metropolitan-area schools and school districts from 1970 to 2010 and found public-school families tend to reside within economically homogeneous neighborhoods where classmates have similar family incomes.

Taken together, this study deepens the question of the inequality of school choice access because students in under-performing schools will be negatively impacted as economic stratification gets worse, even if the choice option exists equally. Therefore, policymakers need to reconsider not just the design of the school choice program but also how students from disadvantaged families who need the support for better education can practically make the best use of this opportunity.

Policy Implications

In an effort to create a school choice program, the Trump administration has advocated the use of vouchers for students to attend private schools (Levesque et al., 2018). Although school choice supporters stress the revitalization of public education based on school competition, others argue that school choice competition contributes another inequity as it could benefit students from middle-class backgrounds whose families use their social capital to reinforce their social class and relative advantage for their children (Ball, 2003; Levin, 2002). As a result, students who remain in the same under-performing schools might be negatively influenced by increasing inequities in the school (Kotok et al., 2015; Levin, 1998).

All in all, results of this study highlight the implementation of school choice programs as well as patterns of utilization by students and families. This study concludes that policymakers should cautiously focus on distribution of opportunity and access by different student and family backgrounds. Future research should investigate the reasons that disadvantaged students, who could benefit from school choice, are not using school-based vouchers and the factors that hinder their usage.

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Corresponding Author: Hyun-Ki Shim
Author Contact Information: hs13e@my.fsu.edu

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Appendices

***Table 4A**. Regression Results Including All Variables, Change in Total Enrollment*

	Model 1	Model 2	Model 3	Model 4
OSP	-4.61***	-4.06***	-4.06***	-5.35***
	(0.68)	(0.77)	(0.78)	(1.36)
Lag				
OSP (n + 1yr)				-2.48*
				(1.10)
OSP (n + 2yr)				-0.30
				(1.13)
OSP (n + 3yr)				-1.84
				(1.18)
School				
Male students (%)		0.07	0.07	-0.06
		(0.05)	(0.05)	(0.09)
White students (%)		0.20*	0.20*	-0.02
		(0.09)	(0.09)	(0.20)
Hispanic students (%)		0.06	0.06	-0.00
		(0.12)	(0.12)	(0.22)
Black students (%)		0.15	0.15	0.20
		(0.11)	(0.11)	(0.19)
FRL students (%)		-0.02	-0.02	-0.01
		(0.01)	(0.01)	(0.01)
Non-ELL (%)		-0.04	-0.04	0.14
		(0.07)	(0.07)	(0.12)
Disabled (%)		0.01	0.02	0.10
		(0.06)	(0.06)	(0.13)
Grade				
B		-0.62*	-0.61*	-0.63
		(0.27)	(0.27)	(0.45)
C		-1.70***	-1.70***	-0.74
		(0.40)	(0.39)	(0.64)
D		-3.19***	-3.22***	-2.35**
		(0.59)	(0.58)	(0.73)
F		-3.32**	-3.39**	-1.39
		(1.13)	(1.13)	(1.60)
District				
White (%)			-0.07	-0.24
			(0.13)	(0.40)
Black (%)			0.15	-0.03
			(0.25)	(0.49)
Population age 5–17 (%)			1.35**	-1.64
			(0.48)	(1.95)

Degree over BA (%)			-31.72	41.86
			(23.29)	(60.96)
Unemployment rate (%)			-0.03	0.02
			(0.13)	(0.44)
Median income (ln)			1.45	9.87
			(5.66)	(18.61)
Year = 2012	-0.91*	-0.34	-0.08	
	(0.36)	(0.24)	(0.32)	
Year = 2013	-0.09	1.35***	1.84***	
	(0.57)	(0.26)	(0.41)	
Year = 2014	-0.63	1.23***	1.98***	
	(0.51)	(0.28)	(0.49)	
Year = 2015	-0.79	1.12**	2.08***	-0.16
	(0.52)	(0.38)	(0.55)	(1.10)
Year = 2016	-1.19	1.19***	2.47***	-0.93
	(0.63)	(0.33)	(0.60)	(1.51)
Constant	1.84***	-11.31	-3710.1	-84.91
	(0.36)	(11.72)	(64.65)	(206.59)
Includes school control	No	Yes	Yes	Yes
Includes district control	No	No	Yes	Yes
District-fixed	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes
Number of schools	11,669	10,264	102,64	4,741
R^2	0.006	0.026	0.026	0.027

Note. Estimated coefficients are rounded to nearest 1/100. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5A. *Regression Results Including All Variables, Change in FRL Enrollment Share*

	Model 1	Model 2	Model 3	Model 4
OSP	1.11	2.35	2.31	0.84
	(0.68)	(1.45)	(1.46)	(2.41)
Lag				
OSP (n + 1yr)				0.29
				(2.17)
OSP (n + 2yr)				-1.27
				(2.26)
OSP (n + 3yr)				-1.74
				(1.64)
School				
Male students (%)		-0.07	-0.07	-0.04
		(0.07)	(0.07)	(0.24)
White students (%)		0.01	-0.01	-0.08
		(0.16)	(0.16)	(0.55)

Hispanic students (%)		0.01	-0.02	-0.07
		(0.17)	(0.18)	(0.54)
Black students (%)		0.10	0.07	0.23
		(0.17)	(0.17)	(0.44)
FRL students (%)		-0.02	-0.02	-0.12
		(0.05)	(0.05)	(0.19)
Non-ELL (%)		-0.11	-0.12	-0.24
		(0.10)	(0.10)	(0.15)
Disabled (%)		-0.07	-0.07	-0.04
		(0.07)	(0.07)	(0.24)
Grade				
B		0.63	0.59	2.49
		(0.53)	(0.52)	(1.68)
C		-0.92	-0.99	-0.77
		(0.57)	(0.60)	(0.84)
D		-0.30	-0.372	-1.675
		(0.94)	(0.97)	(1.74)
F		-2.78	-2.84	-3.63
		(2.19)	(2.24)	(3.37)
District				
White (%)			0.04	-0.56
			(0.34)	(1.85)
Black (%)			0.78	-0.04
			(0.94)	(2.34)
Population age 5–17 (%)			-0.03	0.45
			(2.08)	(7.30)
Degree over BA (%)			-42.81	-294.44
			(114.04)	(381.91)
Unemployment rate (%)			-0.20	-3.39
			(0.62)	(2.93)
Median income (ln)			-10.32	-27.15
			(19.75)	(83.99)
Year = 2012	-0.83	-0.81	-0.85	
	(0.67)	(0.66)	(1.31)	
Year = 2013	-5.07**	-5.00*	-4.08	
	(1.90)	(1.89)	(2.39)	
Year = 2014	-1.39	-1.00	-0.10	
	(1.01)	(1.20)	(2.56)	
Year = 2015	1.56	2.63	2.48	2.39
	(2.05)	(2.49)	(3.38)	(5.59)
Year = 2016	-3.77*	-4.05*	-4.03	-6.57
	(1.63)	(1.63)	(2.67)	(6.37)
Constant	1.53***	5.22	116.03	459.71

	(0.30)	(17.11)	(197.72)	(993.89)
Includes school control	No	Yes	Yes	Yes
Includes district control	No	No	Yes	Yes
District-fixed	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes
Number of schools	11,648	10,261	10,261	4,738
R^2	0.03	0.04	0.04	0.5

Note. Estimated coefficient are rounded to nearest 1/100. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6A. *Regression Results Including All Variables, OSP Cumulative Effects*

	Total Enrollment	FRL Share
OSP eligibility		
First	-4.44***	3.21
	(1.10)	(1.84)
Second	-4.51***	2.36
	(0.98)	(2.11)
Third	-3.04*	-1.32
	(1.16)	(3.42)
Fourth	-2.21	5.58**
	(3.65)	(1.98)
Fifth	-16.2**	5.16
	(5.72)	(3.12)
Sixth	-5.95*	7.84
	(2.79)	(4.32)
School		
Male students (%)	0.07	-0.07
	(0.05)	(0.07)
White students (%)	0.2*	-0.01
	(0.09)	(0.16)
Hispanic students (%)	0.05	-0.02
	(0.12)	(0.18)
Black students (%)	0.15	0.07
	(0.11)	(0.17)
FRL students (%)	-0.01	
	(0.01)	
Non-ELL (%)	-0.04	-0.018
	(0.07)	(0.05)
Disabled (%)	0.01	-0.12
	(0.06)	(0.10)
Grade	-0.60*	0.58
B	(0.28)	(0.50)
	-1.70***	-1.01

C	(0.39)	(0.62)
	-3.22***	-0.39
D	(0.58)	(0.98)
	-2.98*	-3.48
F	(1.24)	(2.57)
District		
White (%)	-0.06	0.04
	(0.13)	(0.34)
Black (%)	0.14	0.79
	(0.25)	(0.94)
Population age 5–17 (%)	1.39**	-0.04
	(0.48)	(2.09)
Degree over BA (%)	-32.47	-43.27
	(23.56)	(114.16)
Unemployment rate (%)	-0.02	-0.20
	(0.14)	(0.62)
Median income (ln)	1.90	-10.37
	(5.78)	(19.66)
Year = 2012	-0.07	-0.85
	(0.32)	(1.31)
Year = 2013	1.84***	-4.05
	(0.41)	(2.40)
Year = 2014	2.00***	-0.09
	(0.50)	(2.58)
Year = 2015	2.14***	2.49
	(0.57)	(3.41)
Year = 2016	2.52***	-4.00
	(0.62)	(2.67)
Constant	-42.39	116.41
	(65.75)	(196.75)
Includes school district control	Yes	Yes
District-year fixed	Yes	Yes
Number of schools	10,264	10,261
R^2	0.023	0.041

Note. Estimated coefficient are rounded to nearest 1/100. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.