Capacity Expansion, Educational Effort, and Dynamics of the Public Education Market

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June 20, 2023

`Preliminary and Incomplete`

Abstract

As the charter school sector grows in the U.S., policymakers have introduced initiatives to designate charter schools with high academic performance levels and authorize them with eligibility to expand enrollment capacity. How do these policies affect overall charter schools' total seats, average performance, and accessibility to low socio-economic status (SES) students? How does the policy influence charter schools' two decisions, capacity expansion and educational effort? And how do these decisions influence traditional public schools' (TPS) educational efforts via spatial competition? I investigate these questions by leveraging one such state-wide policy, the 2011 Florida High-Performing (HP) Charter School Statute. Using a novel dataset tracking 630 Floridian charter and 2411 TPSs from 2007 to 2019, I find a positive policy effect on HP charter schools' capacity and enrollment. Relatedly, TPSs enroll fewer students if surrounded by more HP charter schools. More importantly, many charter schools not designated as HP nonetheless demonstrate high educational effort, measured by teacher-value-added. They generally serve lower SES households and hence do not perform at high enough performance levels to obtain HP designation. I build and estimate a dynamic model of the education market where both types of schools adjust capacity and performance intertemporally and engage in spatial competition. I allow their two decisions, capacity expansion and educational effort, to depend on the HP designation, capacity, performance, competitiveness of local schools, and students' demographics. Estimates reveal that HP designation reduces the adjustment cost when charter schools expand. In a series of counterfactual policy simulations (in-progress), I compare the extant policy to three counterfactual policy situations: no HP designation system , giving additional expansion eligibility to high value-added charter schools, as well as unconditional deregulation of all charter schools.

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1 Introduction

Charter public schools have become a vital element of school choice programs in the United States (Cohodes and Parham 2021). They are free to students and receive public funding according to the number of full-time students enrolled. Despite the controversy in their effectiveness[1], charter schools, high-quality ones in particular, may be considerably capacity-constrained due to the high demand. In Florida, for instance, oversubscription was observed in 61% of charter schools in 2011. Among these schools, 40% received applications exceeding the enrollment target by 1.5 times, with over half achieving the top-tier academic rating of "A." These capacity constraints can be attributed, in part, to regulations governing charter school entry and expansion, similar to those imposed on other highly regulated public-service entities[2]. In response, policymakers have implemented initiatives to designate charter schools with high academic performance levels and grant them eligibility to expand their enrollment capacity[3]. These policies aim to alleviate charter schools' capacity constraints, incentivize more educational effort in improving academic performance, and ensure that expanding designated schools raise the average performance of the charter sector.

However, using mainly schools' performance *levels* as the criterion may be counterproductive compared to using value-added, a measure of schools' contributions to improving students' scores, isolating students' past scores and demographics. Furthermore, the policy may favor charter schools serving households with high socioeconomic status (SES), as they can more easily meet the performance level criterion for designation. More importantly, little is known about how charter schools dynamically make decisions on expansion and educational efforts, and how these decisions influence student outcomes in charter and traditional public schools (TPS).

In this study, I investigate these effects and explore optimal policy designs by examining the Florida High-Performing (HP) Charter School Statute implemented in

[1] Some studies have found that highly effective charter programs lead to improvements in students' test scores and future life choices (Abdulkadiroğlu et al. 2011; Booker et al. 2011; Angrist et al. 2016; Dobbie and Fryer 2020; Cohodes et al. 2021; Cohodes and Feigenbaum 2021). However, other studies have reported only modest (Sass 2005; Hanushek et al. 2007) or even negative effects (Bifulco and Ladd 2007; Imberman 2011)

[2] For example, healthcare providers must obtain special government permission, known as Certificate-of-Need laws, before expanding their services or facilities.

[3] The Race to the Top initiative of the Obama Administration was based in part on the belief that reducing regulatory barriers to entry and school expansion would result in high-performing charter schools serving disadvantaged students. Similar policies have been implemented in Massachusetts (Ridley and Terrier 2018), Missouri, and Louisiana (see the National Association of Charter School Authorizers' 2019 report on "Expanding Access to High-Performing Charter Schools 2019").

2011. To accomplish this, I utilize a novel dataset that tracks the annual operation of charter schools and TPSs and develop and estimate a dynamic model of schools' decision-making. This model allows me to quantify schools' incentives, constraints, local competitive environment, and the adjustment costs associated with expansion and educational effort, which are the two core decisions made by charter schools. Using the model, I can separate and quantify the effect of each economic force on the distribution of student outcomes across charter schools and TPSs and explore alternative policy designs.

The panel data track almost all Floridian regular charter schools (630) and TPSs (2,411) serving K-8 grades from 2006-7 to the 2018-19 school year. Using the data, I found evidence suggesting HP charter schools increase enrollment and the number of classrooms after being designated as HP. Concomitantly, TPSs surrounded by more HP charter schools systematically enroll fewer students, suggesting potentially intensive local competition across sectors. Notably, many charter schools not designated as HP exhibit high mean teacher value-added. These schools typically serve lower SES households and do not achieve the required performance levels for HP designation, despite their high value-added. This pattern suggests that the policy may exacerbate inequality in access to high value-added charter schools for different SES groups by not granting sufficient eligibility (i.e., the designation) for expansion. Lastly, I find evidence that schools' current designation, capacity, performance level, relative competitiveness to local schools, and demographics are critical determinants of their expansion and educational effort (in improving students' or schools' academic performance) decisions. These factors are considered state variables in the structural model, allowing schools' decisions to depend on a rich set of observable heterogeneity.

Based on these empirical patterns, I develop and estimate a dynamic model that links schools' two decisions, capacity expansion and educational effort, to student achievement. Aligned with the data, the model considers HP designation, capacity, performance level, relative competitiveness to local schools, and demographics as the core state variables. This framework enables schools' decisions to depend on these factors, resulting in heterogeneous responses across schools based on local market conditions. In the model, charter schools, competing for students with TPSs, decide how much to invest in the educational effort and capacity expansion over time. Unlike charter schools, TPSs only make decisions on efforts to improve performance while having their capacity fixed. The two decisions are associated with adjustment costs, which consist of particularly both variable costs and fixed costs as capacity changes.

Critically, the policy is considered in the model as follows: charter schools can earn HP designation by achieving good performance, which influences the cost of adjusting capacity. These decisions endogenously change all schools' future capacity and performance levels, influencing their future enrollment via a demand function. Using the model, I can forward simulate the evolution of the distribution of schools' decisions and their implications on performance and capacity distribution across schools. The optimal choices of schools derived from the model form the basis of estimating the underlying model primitives. Building on the recent development in the estimation of dynamic models[4], I use a simulation-based two-step algorithm developed by Bajari et al. (2007) to estimate the model to avoid the computational burden of solving the model directly. The variation in charter and TPS reactions triggered by the policy shock serves as one important source of identification for these effects.

My primary empirical findings from the estimates of adjustment costs are that both educational efforts, measured by mean teacher value-added, and expansion are costly and that the HP designation leads to a marked reduction of adjustment costs when charter schools expand. Given the estimates, I compare the current policy to three counterfactual policy situations (in-progress): no HP designation system, giving additional expansion eligibility to high value-added charter schools, and unconditional deregulation of all charter schools. By investigating the no HP counterfactual, I can quantify the contributions of each economic force to the distribution of all schools' performance and capacity. In particular, weighing the relative importance of the designation system's incentive channel (cost reduction) and its competition channel (pressure from expanding neighbors) on schools' effort decisions and average performance is particularly informative to design better expansion deregulation policies. Further, by considering adding value-added into the extant designation criteria, I specifically target the expansion eligibility inequality of the extant policy and inspect how equalizing the eligibility can induce more expansion of the high value-added charter schools serving the low SES regions. Last but not least, although deregulating all charter schools in their expansion eligibility sounds intriguing, I address the diversity of the objectives education policymakers have and the cost-effectiveness of the comprehensive deregulation from a public economics perspective, borrowing the formula from the critical literature on education finance. Through these evaluations, I provide in-depth scrutiny of the extant policy's implications on schools' average

[4]Recently, Aguirregabiria et al. (2021) and Berry and Compiani (2021) provide comprehensive overviews on this topic in IO.

performance and capacity, charter-TPS competition, and the equality of high-quality education resources across different student groups. Moreover, these evaluations also inform the design of better charter expansion deregulation policies associated with their potential costs.

Related Literature. First and foremost, this study is the first to analyze the policy effects of deregulating capacity expansion for charter schools. Existing literature on charter school expansion focuses almost solely on the impact of entry of charter schools, such as the competitive pressure it places on TPSs (Imberman 2011; Figlio and Hart 2014; Mehta 2017; Gilraine et al. 2021), its consequences for inequality in charter access (Singleton 2019), its effect on racial segregation (Monarrez et al. 2022) and its influence on district budgets for TPSs (Baker et al. 2015; Epple et al. 2016; Buerger and Bifulco 2019; Mumma 2020; Singleton and Ladd 2020). This study leverages a unique policy to demonstrate instead the considerable post-entry dynamics observed in charter schools and employs a structural model to quantify their implications for schools' decision-making and student achievement distribution. Specifically, I examine the policy's impact on the equality of educational resources across different student groups, thereby contributing to the existing literature on school choice that focuses on education equality and allocative efficiency (Hoxby, 2003; Hastine et al., 2009; Campos and Kearns, 2021) by emphasizing the allocation of expansion eligibility and the endogenous decisions resulting from capacity deregulation.

Secondly, I contribute to the growing literature that emphasizes the industrial organization of the supply of education and its implication on student allocation, sorting, segregation, and academic progress (Hasting et al., 2009; Ferreyra and Kosenok, 2018; Mehta, 2017; Singleton, 2019; Dinerstein and Smith, 2021; Neilson, 2021; Allende, 2022). Distinguishing itself from previous studies, this study is the first to address the dynamics, specifically the within-school endogenous changes in both capacity and academic performance. The policy inherently involves intertemporal tradeoffs, as charter schools must accumulate satisfactory performances over multiple years to benefit from the policy. By exploiting this dynamic feature, I provide an innovative framework for analyzing education policies when schools are forward-looking.

Thirdly, this study contributes to a new strand of literature exploring successful charter programs' replication (Tuttle et al., 2015; Cohodes et al., 2021). While existing literature primarily focuses on identifying instructional and management practices for propagating effective charter programs (Zimmer and Buddin 2007; Angrist et al.

2013; Fryer 2014; Cohodes et al. 2021), this study differs in two aspects. Firstly, it examines a state-wide charter policy rather than focusing on a particular locality (Cohodes et al. 2021) or a specific brand of charter schools (Tuttle et al. 2015). Secondly, it also emphasizes the implications of such a policy on the TPS sector.

The remainder of the paper proceeds as follows. Section 2 provides industry background. Section 3 introduces data sources and the sample under inspection. Section 4 shows descriptive patterns about Florida education market and evidence on the policy effects. Section 5 introduces the current version of the quantitative model. Section 6 introduces empirical strategy in estimating the model. Section 7 shows estimates of the model. Section 8 displays simulations based on counterfactual policies (in-progress) and a sketch of an alternative model (in-progress).

2 Industry Background

2.1 The Florida Charter School Market

Florida has one of the largest public school enrollments in both the traditional and charter sectors across all states. It also has sound charter laws and relatively lenient entry screening (Singleton, 2019), making it a state with one of the highest numbers of charter schools and charter enrollment shares in the United States. Additionally, Floridian students can choose any public school or charter school if they are not capacity-constrained through a process known as "controlled open enrollment". These unique features of the Florida public education market amplify the potential impact of policies targeting the charter sector on the overall landscape of public education. Therefore, Florida becomes an ideal state for evaluating the effects of charter school policies.

Regarding accountability, Florida has implemented a system that assesses and gives performance scores to nearly all charter and TPSs annually. This system assigns accountability scores or letter grades to schools, ranging from A (highest) to F (lowest), based on the same criteria applied to both charter and TPS. Notably, while the rating system aims to consider students' achievements and learning gains relative to their previous scores, it still places more emphasis on absolute achievements. This emphasis is evident in the criteria used to assess schools' learning gains, where a school can receive a high score if its students maintain their test scores at a sufficient level, regardless of their individual growth. Among all schools in my sample in the

2018-2019 school year, the letter grade distribution is approximately 34% A, 26% B, 32% C, and the rest 8% D, F, or missing.

2.2 The New Statute and Charter Expansion Management

In July 2011, Florida enacted the High-Performing (hereafter referred to as ”HP”) Charter School Statute, which remains in effect to this day. The statute defines HP charter schools as those with three consecutive years of exemplary performance[5], two As and no grades below B [6] (“2A1B” rule henceforth), marking satisfactory achievement and progress of performance in standardized tests of the students in the school. However, suppose an HP charter school receives two C grades. In that case, its HP designation can be revoked. However, such cases were rare in the sample [7]. Among all charter schools in the sample, approximately 20% held HP designation in 2012, and this percentage increased to 40% by 2019.

The most significant benefit granted by the statute was the authorization for HP charter schools to expand their enrollment capacities without the approval of local school districts. They can increase enrollment capacity once per school year, expand grade span not already served within the range of K-12, or replicate its educational program in any district in Florida[8]. The statute legally prevents local school districts from rejecting these expansion requests made by HP charter schools. On the other hand, districts had the discretion to reject any expansion before the policy's implementation, or after the policy if the non-HP charter schools propose such requests. Hence the policy essentially introduced a new incentive system that links the past performance of charter schools to the automatic eligibility for expansion.

I do not directly observe the enrollment capacity measured in student count as written in charter contracts. Thus, I make a critical measurement assumption that the number of classrooms for instruction in a charter school serves as a sufficient

[5]The statute also requires healthy financial conditions. However, this is easier to be satisfied compared to the performance requirement. For all charter schools meeting the performance criteria, there are few cases in which schools fail to satisfy the financial requirement or an incumbent HP school has been deprived of the designation for financial reasons.

[6]The criterion allows charter schools having two years of A level to be designated after 2017.

[7]In my sample, seven charter schools were de-designated from 2012 to 2019, and 179 charter schools that were designated and never de-designated. Since the de-designated charter schools account for less than 4% of the designated charter schools, I code them as never designated throughout the paper.

[8]Additional benefits for individual HP charter schools include reduced frequency of financial statement reporting to the sponsor, usually the local school district. They also have the opportunity to modify their charter to extend its duration and enjoy a slight reduction in administrative fees.

statistic for enrollment capacity [9]. Leasing is also notable as the primary ownership type of charter schools contract. Leasing is the primary form of ownership for charter schools, and the cost of expanding capacity, i.e., adding classrooms for instruction, is typically associated with leasing more spaces or renovating existing leased facilities that are not yet utilized. Consequently, modifying capacity in this context can be achieved relatively quickly compared to constructing entirely new facilities.

Throughout this study, I interchangeably use the term "the policy" or "the statute" to refer to this event. Moreover, I refer to the years before 2012, the "pre-policy" period, and the year 2012 and onward, the "post-policy" period.

3 Data and Sample

To conduct this research, I combined digitized government documents, publicly available datasets, and those with limited public access that require requests for disclosure of information. I collected enrollment of each grade and race, location, and activity status, for all public schools in Florida from the National Center of Education Statistics' ELSi dataset, which was merged into the Florida School Master File to obtain additional school characteristics. The locations of schools were mapped to census tracts whose geocodes were merged with U.S. Census Bureau's American Community Survey to acquire granular local demographics for all schools. The school's location is also valuable for providing the distance students need to travel from each census tract to a particular school and identifying which schools are closely competing with it. I collected schools' performance information, the letter grades, detailed component scores used to produce the letter grades, and standardized test scores from Florida School Grades Archives and the Department of Education's Bureau of K-12 Assessment.

To tailor the analysis to the policy context, I requested and obtained characteristics such as capacity (number of classrooms and buildings), lease, mission statement, education model, management company, staff details, and annual waitlist status of charter schools from Florida charter schools' annual Accountability Reports from the Florida Office of Independent Education and Parental Choice. From the same source, I obtained the annual HP designation status (designated, de-designated). With all

[9] In this context, enrollment capacity refers to the maximum number of students a charter school can enroll. It should not be confused with facility capacity, which represents the maximum number of students the school's physical facilities can accommodate safely. Naturally, enrollment capacity cannot exceed facility capacity, although the two quantities are correlated due to the costs associated with leasing or owning additional facilities that remain unused.

these variables, I can characterize a complete history of the supply side by each charter school's capacity, performance, designation, local demographics, and traditional competitors that can be mapped to its enrollment volume and composition. These can also be done for TPSs. Additionally, I requested and obtained annual teacher-subject level value-added estimates from a regression-based statistical model run by the Florida Department of Education. I aggregated them to the school level according to the teacher-school linkage provided by the same dataset to measure the educational effort in improving a school's performance level, one of the crucial investment decisions in the model. Lastly, I acquired charter schools' revenue, itemized expenses, and assets, digitized by Singleton (2019) from independent audits filed annually with the Florida Auditor General. I extended the original dataset by adding more years and coverage of schools. The expenditure can be conveniently employed in estimating the operating cost function in the quantitative model.

The analysis focuses on regular traditional and charter schools that serve elementary (K-5) and middle grades (6-8) in Florida from 2007 to 2019 [10]. These selected schools encompass the majority of K-8 public schools and their enrollment in Florida. Schools operating grades from kindergarten to 8^{th} yet running concurrently high school grades (the 9^{th} to 12^{th} grade) during the sample period are excluded. This exclusion was necessary due to the distinct accountability requirements for high schools, which differ from those of elementary and middle schools. By excluding these schools, the statistical analysis becomes more convenient, and the interpretation of the schools' performance score production function becomes more transparent. Thus around 7% of the total K-8 students are not considered during the sample period.

The ultimate sample under examination has 2,411 TPS and 630 charter schools, whose observation counts are 29,333 and 4,483, respectively, at the school-year level. Comparing the sample length (13 years), the median panel length of TPS and charter observations is 12.2 and 7.28 years, respectively.

4 Preliminary Evidence

I document descriptive evidence concerning the spatial distribution of HP charter schools and the suggestive policy effect associated with the change in the spatial distribution of enrollment, capacity, performance, and student composition across

[10]Regular schools in my selection are all public schools excluding those that are laboratory, municipal, virtual, providing special education and those charter schools conversed from a TPS.

all schools. For ease of exposition, when describing a school year, I use “2019” to represent the “2018-19 school year.”

4.1 Overview of Traditional and Charter Sector

In my sample, charter enrollment accounts for an increasingly more share of the public K-8 enrollment overtime: 3.3% in 2007, 6.5% in 2011, and 11.4% or around 210,000 students in 2019. The number of charter schools in my sample is increasing, too: 216 in 2007, 290 in 2011, 397 in 2015, and 436 in 2019. After 2012, the charter sector’s exit rate in my sample remained stable at around 3% to 5%, while the entry rate started to drop from around 18% in 2011 to 5% in 2019 [11]. Typically, they are more in the count and more densely distributed in school districts with higher population and population density, usually highly urbanized regions. In these large school districts, charter schools account for a higher share of public enrollment (around 20%) and tend to proximate closer to other charter and TPSs than other districts.

Zooming in on the charter sector, in Table 1, I comprehensively compare the average outcomes (and the standard deviations in the parenthesis) of the non-HP and the HP charter schools in 2015, 4 years after the enactment of the policy. In 2015, among 376 charter schools in my sample, 31.6% were HP: 69 were designated in 2012 and 50 in 2013-15. On average, compared to the non-HP ones, HP charter schools have higher performance scores, capacity, and enrollment. They are in census tracts with higher population density, income, students’ test scores, and a more white or Hispanic population. Consistent with the demographics of their locations, they, on average, serve more white and Hispanic students while enrolling systemically fewer disadvantaged groups, including black students and those eligible for free or reduced-price lunch.

4.2 Charter Expansion and Enrollment Change of TPSs

Charter Expansion. As shown in Table 1, both types of charter schools increase capacity on average. For the non-HP charter schools, the average increase of classrooms from 2007 to 2011 (pre-policy increase) and from 2011 to 2015 (post-policy increase) are close, at around 3.4 classrooms. For the HP, these increases are larger

[11] Exit rate in year t is defined as the ratio between total exits in t and count of charter schools in t. The entry rate is the ratio between the total entries in t and the count in $t-1$. An exit is labeled as in year t if I do not observe enrollment records ever since $t+1$. Moreover, an enter is labeled as in year t if I start to observe a charter school’s enrollment record since t but do not observe enrollment record before t.

Table 1. Summary Statistics for the non-HP and HP Charter Schools in 2015

	non-HP	HP		non-HP	HP
I. School Characteristics			III. Student Composition		
Total Performance Score (%)	0.50	0.72	Percentage of Free/ReducedPrice Lunch	0.52	0.40
	(0.16)	(0.12)		(0.30)	(0.27)
Enrollment	357.25	560.24	Percentage of Hispanic Students	0.32	0.43
	(330.20)	(349.40)		(0.28)	(0.32)
Number of Classroom	21.88	33.04	Percentage of Black Students	0.31	0.13
	(16.90)	(19.41)		(0.31)	(0.19)
II. Location (Census Tract) Characteristics			Percentage of Whilte Students	0.31	0.38
Population Density (1000/square mile)	1.29	1.53		(0.28)	(0.30)
	(0.88)	(1.00)			
			IV. Increase of Classrooms		
Household Income	62755.03	68443.73			
	13625.40	19158.80	Classroom Increase from 2007 11	3.40	4.36
				(8.07)	(9.92)
Average Standardized School-level Reading Score of All Schools within 5 Miles	-0.23	-0.04			
	(0.51)	(0.53)	Classroom Increase from 2011 15	3.55	5.69
				(9.48)	(11.84)
Average Standardized School-level Math Score of All Schools within 5 Miles	-0.19	0.01			
	(0.49)	(0.53)			
Percentage of White Population within 5 Miles	0.73	0.79			
	(0.14)	(0.12)			
Percentage of Black Population within 5 Miles	0.22	0.17			
	(0.13)	(0.12)			
Percentage of Hispanic Population within 5 Miles	0.29	0.39	Number of Observations	257	119
	(0.22)	(0.29)			

and more so post-policy. A closer look at whether the HP charter schools did increase capacity can be seen by running an event-study regression represented by the specification in (1) using charter schools' observations [12].

I regard HP designation status as the focal event for a charter school. Here, the unit of observation is a charter school-year, and i and t denote a charter school and a year, respectively. The outcomes of interest, Y_{it}, of charter schools are capacity and enrollment. To account for individual heterogeneity constant across time and state-wise time-invariant shock, I control for school and time fixed effects by FE_i and

[12] I do not include observations that are within the first three years of operation in the regression because expansion in this period is usually negotiated before charter schools enter; hence not subject to the expansion benefit HP policy provides. I coin this period in the life cycle of a charter school the "development phase". In the development phase, charter schools add classrooms gradually according to the expansion plan written in the initial charter. And normally, enrollment grows much faster in the development phase than in later years. This can be shown simply by plotting the average enrollment of charter schools against their age. One can notice the significant slowing down of enrollment growth after charter schools pass the development phase by simply eyeballing. However, it is more important to point out that since one needs three years of performance levels to be designated, every charter school is not designated as HP in its first three years of operation. Therefore, without excluding these observations, one exaggerates the expansion increase in non-designated periods of charter schools.

FE_t. The set of relative period dummies $1_{\{t-E_i=\ell\}}$ indexed by ℓ, indicates whether a certain calendar year t is ℓ-year relative to the designation year E_i of the charter school i. Charter schools that never get the designation are coded as effectively infinity for their designation years. When ℓ is zero, the corresponding dummy equivalently means whether an i is in its year of designation. Hence, I call the relative period dummies when $\ell < 0$ the "pre-designation" dummies and "post-designation" dummies when $\ell \geq 0$. The relative period ℓ can maximally range from L_{min} to L_{max}. In a sample spanning from 2007 to 2019, L_{max} is 7 ($7 = 2019 - 2012$) and L_{min} is -12 ($-12 = 2007 - 2019$) given the policy was effective starting in 2012. I include covariates X_{it} to represent controls such as the local market conditions.

$$Y_{it} = FE_i + FE_t + \sum_{\ell=L_{min}}^{L_{max}} \beta_\ell 1_{\{t-E_i=\ell\}} + \gamma X_{it} + \epsilon_{it} \tag{1}$$

The core parameters of interest are β_ℓs. They offer a graphical view on the dynamics of the designation effect and hence are useful in showing the variation in the expansion behaviors of charter schools associated with the policy. However, I do not intend to causally identify the treatment effects (potentially dynamic and heterogeneous) of HP designation on outcomes because it is endogenous by design.

In Figure 1, each sub-graph plots the point estimate of β_ℓ (the y axis) with respect to relative period index (the x axis) and the 95% confidence intervals of β_ℓs under different outcomes. I use the sample from 2007 to 2015 to show the result in the classroom because the current charter capacity data are problematic after 2015. The results suggest that designated charter schools increase the number of classrooms and enrollment on average by a significant amount, and the change normally starts after the first year of designation. The estimates for β_ℓ when $\ell > 0$, are, on average, 2.5 classrooms, a non-ignorable magnitude given that the sample average of charter classrooms in 2011 is only around 20. Further, by inspecting the enrollment as the outcome using the sample from 2007 to 2019, the enrollment increases match capacity increase, with estimates of β_ℓ when $\ell > 0$ valued around 40-50 on the +1 and +2 post-designation dummies. The sample average of charter 2011 enrollment is around 331. The estimates on the longer post-designation dummy show that the enrollment gap between the HP charter schools and other schools in later years is weaker. There is no indication of the pre-trend difference in the coefficient's estimates as shown by both graphs. Therefore, the message is clear that designation is associated with more facilities and students.

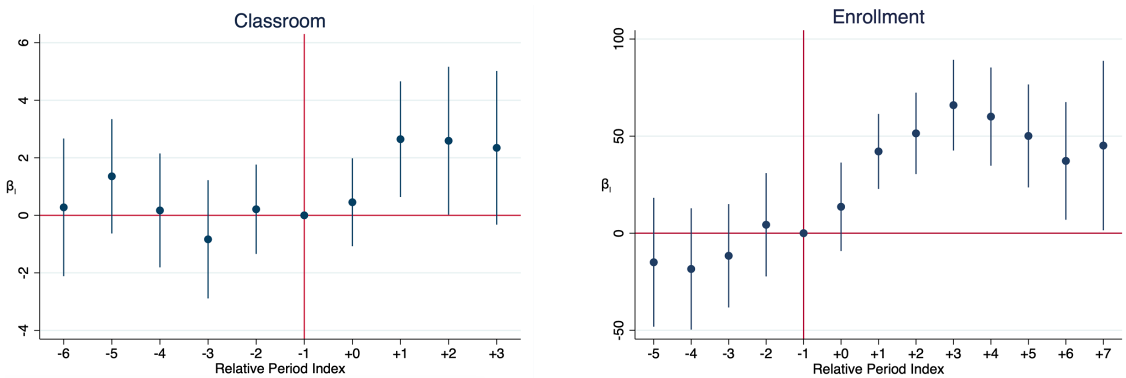

Figure 1. Coefficient Plots of β_ℓs for Classroom Count $2007-15$ and Enrollment, $2007-19$

Enrollment Change of TPSs near HP Charter Schools. Table 2 shows evidence of the reallocation of enrollment associated with the policy. To have a clear view of the reallocation, I inspect only two groups of charter schools in the pre- and post-policy periods. The first group, the "2012-HP," consists of the earliest generation of HP charter schools which were the first to be directly affected by the policy, i.e., received the designation in 2012. The second group, the "Never-HP," consists of those never designated through and including 2019. Within each group, I take the average outcome within a school group in all post-policy years and all pre-policy years. In the "2012-HP" group, charter schools have a higher average enrollment increase relative to their pre-policy outcome, around 40 students (or 11% of the enrollment of the average charter school in 2012), than the "Never-HP" group. Additionally, the average enrollment of all TPSs within 3 miles of a charter school in the "2012-HP" group has dropped by around 57 students, more than the drop in the average enrollment of schools in the "Never-HP" group.

Table 2. Average Enrollment Statistics of the Two Groups of Charter Schools in Two Periods

	Own Enrollment		Mean Enrollment in the Nearby TPSs	
	Pre-policy	Post-policy	Pre-policy	Post-policy
2012-HP	507	604	796	739
Never-HP	263	323	691	682

The reallocation of students across sectors can be further seen via regressions represented by Table 2. It exploits the cross-sectional and intertemporal variation of the exposure to HP charter schools faced by TPSs. The cross-sectional variation of HP exposure comes from the spatial heterogeneity of the existence of HP charter schools. In contrast, the intertemporal variation comes from the policy implementation and the increase of HP charter schools as time passes. To see the effect, I regress log enrollment of TPSs on the exposure of HP charter schools within ($HPexpoband1_{it}$) and that in 3 to 5 miles ($HPexpoband2_{it}$), controlling for school fixed effect and local demographics (D_{it}) faced by the TPS from 2007 to 2019. Columns 1 and 2 show results when using the count of HP charter schools as the exposure variable, while columns 3 and 4 show results using the total capacity of neighboring charter schools, considering potential expansion behaviors post-designation. In columns 2 and 4, I control for local demographics. They show that TPSs' loss of enrollment is associated with more existence of capacity than the neighboring HP charter schools.

$$Logenrollment_{it} = \beta_1 HPexpoband1_{it} + \beta_2 HPexpoband2_{it} + D_{it} + FE_i + \epsilon_{it} \quad (2)$$

These patterns suggest that the charter sector did respond to the policy and that the HP charter schools did impose an externality on the nearby TPSs via reallocation of enrollment. Therefore, competitive spillover is crucial to factor in evaluating the policy effects.

Table 3. Effects on Log Enrollment of Exposure to HP Charter Schools

	(1) Count	(2) Count	(3) Capacity	(4) Capacity
HP Charter 0-3 Miles	-0.011***	-0.012***	-0.00034***	-0.00030***
	(0.001)	(0.002)	(0.00010)	(0.00010)
HP Charter 3-5 Miles	-0.011***	-0.013***	-0.00015**	0.00001
	(0.001)	(0.001)	(0.00007)	(0.00007)
Constant	6.486***	6.485***	6.48588***	6.47099***
	(0.003)	(0.027)	(0.00258)	(0.02719)
Observations	29,037	29,037	29,037	29,037
R-squared	0.940	0.940	0.93898	0.93927
School FE	Y	Y	Y	Y
Control	N	Y	N	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.3 Student Composition and Value-added of HP Charter Schools

As shown in Table 1, HP charter schools appeared more in regions with higher SES. This raises a question: Would charter schools that serve low SES regions get designation by exerting higher value-added, reducing the systematic performance difference observed in Table 1? The following figures show that such differences might systematically root in the designation criteria.

In Figure 2, I show the density of specific indicators of student compositions within a charter school among all charter schools with higher-than-median value-added in 2015. This figure therefore illustrates, among charter schools pay relatively high effort, how is the student composition across the non-HP and HP charter schools. The two indicators are the percentage of students with free or reduced-price lunches (left) and the percentage of black students (right), the two relatively disadvantaged student groups. From Figure 2, among the higher-than-median value-added charter schools, the non-HP tend to serve poor or black students, as the non-HP density curve of these percentages of disadvantaged students is on the right of the HP's curve. The reason could be that the designation criterion, namely "2A1B", relies heavily on the *level* of academic performance of charter schools, less on the *value-added*. This favors charter schools in high SES regions where their students come from more educated families.

This raises a concern about whether the policy could lead to unequal allocation of expansion eligibility, which might result in unequal access to high-quality charter school seats across regions with different SES. Giving charter schools serving the low SES regions with high value-added the opportunity to expand might help reduce the inequality of high-quality charter programs across regions.

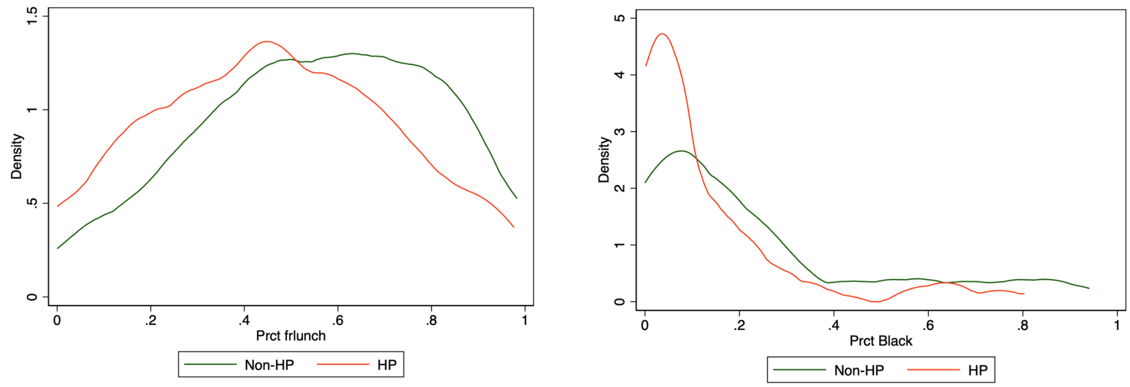

Figure 2. Density of Student Composition Across Higher-than-median Value-added Charter Schools in 2015

5 Quantitative Model

To evaluate alternative policies that may be considered in future reforms, one must carefully model schools' incentives, constraints, and the adjustment costs of expansion and performance upgrading. It is critical to understand the *extent* to which the HP charter schools, as well as under-performing non-HP charter schools, would react to an alternative policy by expanding capacity and upgrading performance, as well as *how much* these decisions would influence the outcome benchmarks (e.g., total charter seats, charter sector performance, equality of HP charter access, and TPSs' decisions, enrollment, and student composition) via competitions across both charter and TPSs.

Informed by the institutional backgrounds and data patterns, a model of schools' decision-making should have the following features. First, schools are forward-looking. The decisions on performance upgrading and capacity expansion have a lasting effect on schools' future capability of attracting and containing students. Additionally, modeling schools as myopic is inconsistent with the need to analyze the policy effect since the policy inherently links the future eligibility of expansion with the performances of charter schools. Second, schools' decisions should depend on spatial heterogeneity. This dependence is critical to understanding the distributional effects on school reactions due to a counterfactual policy change. For example, policymakers might be interested in changing the extant policy to increase the expansion of the charter schools that exert high upgrading efforts and serve the regions where disadvantaged students are. Third, competition across schools should influence student flows and schools' decisions. It is consistent with the extant literature (Mehta 2017; Singleton 2019; Dinerstein and Smith 2021) and suggestive evidence by the observed reallocation across schools associated with the policy that local competitive pressure should be modeled explicitly. Last, the policy should be modeled as linking the difficulty of increasing charter schools' capacity with their HP designation.

In this section, I present a quantitative dynamic model on how charter and TPSs decide to upgrade performance and expand capacity intertemporally. I allow schools' decisions to depend on a rich set of heterogeneity, such as local market conditions and the intensity of the local competition. I model the policy as introducing a designation status of charter schools that can influence their adjustment cost in capacity expansion. I do not model the entry and exit dynamics of charter schools to emphasize the focus on the post-entry operation of charter schools in terms of their performance and capacity and their competitive interactions with the neighboring TPSs.

Set-up. In this model, schools endogenously expand and upgrade their performance to maximize their long-term objectives. Within each operating period, schools enroll students according to their performance, capacity, and local market conditions, such as demographics and competitive pressures from surrounding schools. Enrollment brings revenue with a fixed reimbursement rate and incurs school operating costs each period. Across periods, schools make costly adjustment decisions that influence future states. The HP designation for charter schools specifically can be earned by charter schools' accumulating good performance and can reduce the cost of adjusting capacity. In the following, I introduce all the state variables and their role in the model.

The building block of this model is a local market faced by a generic school. I assume that time is discrete, denoted by t. t=1,2,3, ..., ∞. In each period t, for the school, it is fully characterized by the following state variables, denoted as

$$(s_t, \epsilon_t) = (\underbrace{o}_{\text{type}}, q_t, k_t, hp_t, d_t, n_t, \epsilon_t).$$

Except for the ϵ_t, other state variables are observable to the econometrician. The unobserved heterogeneity ϵ_t allows gaps between the model-predicted and observed choices.

The time-invariant state o denotes school type, which takes binary values 0 or 1, indicating TPS and charter school, respectively. To model school type explicitly corresponds to the institutional backgrounds that the government regulates TPSs and charter schools differently, and their decision makers are distinct. This setting essentially allows school type to govern different constraints on the state and action space of the school and its objective. Accordingly, all the parameters in the following are allowed to be different according to the type of school in estimation.

The state variables q, performance, and k, capacity, influence the school's enrollment amount, hence the within-period revenue and operating costs. They are the core endogenous variables directly influenced by the school's decisions.

I include the state variable hp, the HP designation status, and allow it to influence the dynamic adjustment cost in the capacity k. With this setting, I model the policy as reducing the adjustment cost in expanding capacity for the HP charter schools. Consistent with the institutional setting, the performance q and HP status are the two determinants for the future HP status. This structure naturally introduces an interaction between the evolution of performance and capacity.

The state variable d and n characterizes the spatial heterogeneity the school faces. They represent local demographics and the competitive threat the neighboring schools put on the school. Both state variables influence its enrollment and demographic composition, hence the within-period revenue and operating costs. I do not model charter schools' entry and exit and assume d to exogenously evolved, independent of a school's decisions. Nonetheless, I allow the local competitive threat to be endogenously influenced by the school's decisions. This assumption reflects the reality that the competitive threat from the neighboring schools can evolve intertemporally and reacts to the schools' actions. Revealing the competitive response from local schools has been a critical theme. Additionally, as preliminary patterns suggest, competition is critical in evaluating the policy effects, especially on how students choose across school sectors and how all schools react to the policy. However, including competition in a dynamic model has yet to be discussed in empirical IO literature on schooling markets. As a first attempt, I, therefore, assume the belief on the competitive threat imposed by the neighboring schools as follows:

Assumption . *Each school's belief in neighboring schools can be summarized by the state variable n.*

Under this assumption, the model is essentially a single-agent dynamic model. Because the decisions schools are allowed to depend on other schools' states or actions only via this comprehensive state variable n. In the future version of this paper, I will use a heterogeneous agent demand model to micro-found the measurement of

n, discussed in the discussion section. In the current version of the model, I only regard n as a demand shifter faced by the school measure it simply using the average performance of nearby schools, discussed in the following section. In the following, school subscripts are suppressed.

Flow Utility and Decisions. Schools make two adjustment decisions, educational effort, or equivalently the amount of value-added v, and capacity expansion e, to maximize expected utility over time. TPSs are assumed to have a fixed capacity, i.e., $e_t = 0, \forall t$, and can only decide on value-added. These adjustments are costly and they jointly influence all the endogenous variables hence the flow utility.

To highlight the core economic interactions while still highlight the difference in the objectives of different types of schools (Mehta, 2017), I assume charter schools care only about profit [13] and has the following flow utility

$$u_t = rE(s_t) - \Psi(E_t, s_t) - \Gamma(v_t, e_t, hp_t, \epsilon_t).$$

Here, u_t represents flow utility at t. It consists of three parts. The first part, $rE(s_t)$, characterizes the funding r injected by the state government into the school per enrollment. It is the primary source of revenue for all schools. The rate r is assumed to be known to econometricians and can be directly obtained from Florida law. The second part, operating cost function $\Psi(.)$, captures the variable cost of maintaining daily operation and instruction, e.g., teachers' salary, renting, staffing, and maintenance. The functional forms of $E(.)$ and $\Psi(.)$ will be exploited during estimation. The third part, $\Gamma(v_t, e_t, hp_t)$, denotes the adjustment costs of capacity and performance across periods. While for TPSs, I assume they care only about enrollment and adjustment cost

$$u_t = rE(s_t) - \Gamma(v_t, \epsilon_t).$$

Having utility to depend on enrollment explicitly allows us to model the potential non-profit nature of charter schools and TPSs.

I assume the adjustment cost function of charter schools has the form in (3):

$$\Gamma(v_t, e_t, hp_t) = \gamma_v v_t + 1_{\{e_t \geq 0\}} (\gamma_1 + \gamma_2 hp_t + \gamma_3 e_t + \gamma_4 e_t \times hp_t) + \gamma_5 1_{\{e_t < 0\}} e_t. \tag{3}$$

[13] All charter schools in Florida operate as a non-profit organization, yet many charter schools sign contracts with private management companies to operate the daily business. The pressure of making a profit may come from payments to these private companies. In Singleton (2019), for-profit charter schools are defined similarly and the structural estimates of the paper show this type of charter schools care more about operating cost than other type of charter schools.

The adjustments are associated with two decisions, $v(.)$ and $e(.)$. They are both mappings from states (including the ϵ_t) to actions:

$$v : s_t \to v_t$$
$$e : s_t \to e_t.$$

The action v_t represents value-added, summarizing schools' input into educational effort (e.g., expenditures on the professional development of teachers, teacher coaches, administrative supports) particularly in improving students' test scores. The action e_t is the school's extra capacity to add (or shrink) in period t. Both actions involve variable costs that depend on the magnitude of the actions, as captured by γ_v, γ_2, and γ_3. Additionally, the HP policy is modeled as influencing adjustment cost in expansion: $\Gamma(.)$ depends on designation status hp_t via γ_3. Additionally, I consider the capacity adjustment, i.e., expansion or shrinkage, as a costly negotiation and renovation process for schools. This corresponds to expenditures in purchasing furniture, planning, hiring lawyers for contracting to lease extra classrooms and lengthy negotiations with the local district, etc. To model some of these spendings that are independent of the magnitude of expansion, I add fixed costs of changing capacity into the adjustment costs via γ_1 and via γ_4, allowing HP status to influence the fixed costs. Introducing the fixed costs hence captures the lumpiness in adjustment in capacity, as observed in the data.

The adjustment cost functions for TPSs are:

$$\Gamma(v_t) = \gamma_v v_t \tag{4}$$

Transitions. For the transitions of the endogenous state variables, capacity evolves in a deterministic way as:

$$k_{t+1} = k_t + e_t.$$

Performance evolves by mapping the current Performance and the value-added into the next period performance, captured by the function: $\tau(.)$:

$$q_{t+1} = \tau(v_t, q_t).$$

In the application, this corresponds to the following production process of academic performance: Students come and perform in standardized tests, earning the school a rating of q_t in period t. And the school decides to put in v_t amount of value-added to promote students' academic performance in $t+1$, resulting in schools earning q_{t+1}.

As for the designation, it evolves as if it depends only on period t's performance level and the HP status, namely:

$$hp_{t+1} = \eta(q_t, hp_t).$$

Note that I regard hp_{t+1} as a passively evolving endogenous variable unaffected by actions *directly*. This assumption reflects the nature of the statute that designation is not dependent on value-added directly.

As for the state variable that represents spatial heterogeneity, namely d_t and n_t, I assume that d_t follows the first-order Markov process and that n_t is influenced by the following function:

$$n_{t+1} = \nu(v_t, e_t, s_t).$$

This captures the competitive spillover a school poses on its surrounding schools in a reduced-form transition function. I allow this spillover be realized both through value-added as well as potentially through charter schools' expansion.

Dynamic Programming. With all model components specified, the maximization problem faced by a charter school is summarized by (5):

$$\begin{aligned}
V(s_t, \epsilon_t) = \max_{v_t, e_t} & \, rE_t(s_t) - \Psi(E_t, s_t) - \Gamma(v_t, e_t, hp_t, \epsilon_t) + \beta \mathbb{E}_{\epsilon_t} V(s_{t+1}|s_t, \epsilon_t) \\
s.t. \quad & (s_{t+1}, \epsilon_{t+1}) = (o, q_{t+1}, k_{t+1}, hp_{t+1}, d_{t+1}, n_{t+1}, \epsilon_{t+1}) \\
& q_{t+1} = \tau(v_t, q_t), \;\; k_{t+1} = k_t + e_t, \;\; hp_{t+1} = \eta(q_t, hp_t), \\
& n_{t+1} = \nu(v_t, e_t, s_t), \\
& d_t \text{ follows Markov Process, } \epsilon_t \text{ follows i.i.d normal distribution.}
\end{aligned} \tag{5}$$

The maximization problem faced by a TPS is summarized by (6).

$$\begin{aligned}
V(s_t, \epsilon_t) = \max_{v_t, e_t} & \, rE_t(s_t) - \Gamma(v_t, \epsilon_t) + \beta \mathbb{E}_{\epsilon_t} V(s_{t+1}|s_t, \epsilon_t) \\
s.t. \quad & (s_{t+1}, \epsilon_{t+1}) = \big(o, q_{t+1}, \bar{k}, \bar{hp}, d_{t+1}, n_{t+1}, \epsilon_{t+1}\big) \\
& q_{t+1} = \tau(v_t, q_t), \\
& n_{t+1} = \nu(v_t, s_t) \\
& d_t \text{ follows Markov Process, } \epsilon_t \text{ follows i.i.d normal distribution.}
\end{aligned} \tag{6}$$

For both types of schools, the expectation operator on the value function is taken due to the stochastic nature of the belief about the next period states.

Given the model construct, the HP policy is considered as two features. First, charter schools can earn HP designation in future periods by increasing performance. Second, the earned designation can influence the adjustment cost of expansion.

The solution to the dynamic programming problem is two policy functions that map state vector s_t to a real number: v_t and e_t. Since s_t includes unobserved heterogeneity ϵ_t, this characterizes the gap between the seemingly sub-optimal observed choices and the predicted optimal choices from the model.

Timing. For a school, the timing of the events between t and $t+1$ is depicted as follows:

1. The aggregate state in period t, namely the s_t, is known by each school. The unobserved shock ϵ_t is privately known by the school.
2. Students choose schools according to s_t, resulting in enrollment for the school, E_t.
3. Knowing E_t, the chooses two actions, v_t and e_t given s_t and ϵ_t
4. Flow utility u_t in period t is realized for the school
5. The state s_t evolves to its new level s_{t+1} according to v_t and e_t and the transition rules.

Analysis The model allows for decisions of both charter and TPSs to be responsive to spatial demographic heterogeneity d. To see this, note that $E(.)$ and $\Psi(.)$ can depend on local demographics, as is also pointed out in Singleton (2019). Educating students with low SES can involve higher operational expenditure. This dependence on local conditions can help evaluate the distributional effects of various demographic conditions across different regions from a potential counterfactual policy change. Specifically, an alternative policy that increases the expansion of charter schools (while potentially maintaining their educational effort) in low SES regions can help mitigate disparities in access to high-quality educational resources.

Moreover, because competitive threat enters the demand function, schools' decisions can respond to local competitive threats from other schools. This response further encourages local schools to change their efforts, as captured through the transition of the mean performance of neighbors, n_t. These mechanisms help measure the spillover effect on schools, i.e., the extent to which neighboring schools' efforts influence the schools' effort and how these spillover responses will subsequently impact enrollment across schools. This corresponds to a crucial empirical observation: the reallocation of students across schools as the local competitive environment changes.

Additionally, the model also directly introduces the HP designation hp, which enables the evaluation of the direct policy effect by comparing the observed outcomes of interest to the predicted ones when the designation-related benefits and transitions are eliminated. In the model, this benefit changes the adjustment cost $\Gamma(.)$. Non-HP charter schools can accumulate high performance q to change their HP status in future periods, thereby reducing the adjustment cost for expansion. This setting naturally interacts with the two decisions of charter schools. Furthermore, since investing in effort has lower future costs for expansion, the effort choices of charter schools can be influenced accordingly. This change in the effort will also contribute to the aforementioned spillover effect across schools, resulting in more schools altering their behaviors during different policy implementation periods.

6 Empirical Strategy

In this section, I discuss the estimation strategy, measurements, estimation sample, empirical specifications, and identification.

6.1 Estimation Strategy

As explained in the dynamic programming problem (5), the reimbursement rate r can be achieved directly from the laws, and the discount rate β is set to be a known value as is commonly done in the literature. The rest of the model primitives to be estimated are the enrollment function $E(.)$, operating cost function $\Psi(.)$, adjustment expenditure function $\Gamma(.)$, and the transition functions $\tau(.)$, $\eta(.)$, and $\nu(.)$. Among these primitives, parameters in $\Gamma(.)$ are the only "dynamic parameters". To estimate $\Gamma(.)$, I use the simulation-based algorithm developed by Bajari et al. (2007), henceforth referred to as BBL. They propose a two-step procedure that avoids directly solving the policy functions of the agents in conducting estimation.

In the first step, I pick appropriate functional forms to estimate the demand, operating cost, policy functions, and transition functions. In this step, I essentially characterize the agents' decisions and flow utility as functions of the state variables. In the second step, BBL propose to use the estimated policy functions in the first stage, denoted as $\hat{v}(.)$ and $\hat{e}(.)$, and their perturbed versions $\tilde{v}(.)$ and $\tilde{e}(.)$ to compute the expected discounted sum of the flow utility for large enough periods T. The estimator will search for the parameter $\hat{\Gamma} = (\gamma_v, \gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5)$ of the function of $\Gamma(.)$ that minimizes the profitable deviations with perturbed policy function $\tilde{v}_j(.), \tilde{e}_j(.)$ from the optimal policies estimated in the first stage

$$\min_{\hat{\Gamma}} \sum_j \sum_i \min\{0, \bar{V}(s_{i0}; \hat{v}(.), \hat{e}(.); \hat{\Gamma}) - \bar{V}(s_{i0}; \tilde{v}_j(.), \tilde{e}_j(.); \hat{\Gamma})\}^2, \tag{7}$$

where

$$\bar{V}(s_{i0}; v(.), e(.), \hat{\Gamma}) = \frac{1}{NS} \sum_{ns} \sum_{t=0}^{T} \beta^t u(s_{it}; \hat{\Gamma}) \text{ s.t. } v(.) \text{ and } e(.) \text{ governs the evolution of } s_{it}.$$

Here, i denotes a specific initial state randomly picked, and j indexes a perturbed policy function that slightly and randomly changes the actions predicted by $\hat{v}(.)$ and $\hat{e}(.)$. Note that an ns indexes a simulation. This justifies the calculation of the *expected* discounted sum. For TPSs, the same procedures follow, although only γ_v is estimated in the second stage.

6.2 Measurement

In this section, I integrate the measurement of relevant variables, their availability, and how they evolve over time in the model in Table 4. Unless specified otherwise, all measures are available throughout the sample period. It is important to note that the incomplete coverage of variables v_t and Ψ_t does not affect the estimation of the policy function for educational effort and the operating cost function.

In our model, a period corresponds to a school year, where the label for the year follows a format where the 2013-2014 school year is labeled as $t = 2014$. Each school in the dataset is identified by a unique school ID.

Contents in Table 4 are intuitive and have already been used in providing the preliminary empirical observations. Part A summarizes the state variables on spatial heterogeneity. I construct the local demographics using the American Community Survey 5-year Data Profile, where the middle year of the 5-year data serves as the label for a specific variable. I use household income and racial proportion to represent the spatial heterogeneity in demographic composition and the population of ages 5-14 to represent the market size. Part B summarizes the state and decision variables of schools. I calculate the average teacher value-added score within a school to measure educational effort. Additionally, I consider the accountability score in the last year of t as the performance state variable in t. This choice is motivated by the fact that schools and students are unaware of the schools' accountability scores for the upcoming school year during the recruitment season of the previous year. Hence, the accountability score in the previous year is a more suitable measure variable for the contemporaneous performance state [14]. As for the capacity measure of TPSs, although I do not have the number of classrooms directly, I impute a TPS's capacity by using the largest enrollment observed in a school divided by 22. This choice is reasonable because TPSs are not often capacity-constrained and are subject to regulated middle school class size of 22 students per classroom[15].

6.3 Estimation Sample

The sample used for structural estimation consists of a selected set of charter and TPSs from the full sample. First, I exclude schools that only run grades from K-2 for most of the sample period, those with a short sample length, or schools with a small average enrollment per grade. These exclusions are necessary as these schools may have objectives that differ significantly from the rest, and missing variables are often systematically associated with them. For example, schools that constantly run K-2 do not participate in standardized tests and hence do not have a reliable source of performance evaluation.

Furthermore, I exclude specific observations from charter schools. When estimating the policy functions of charter schools, I only include observations from charter schools that have been operational for more than three years. This selection criterion aligns with the model's focus on characterizing the relatively mature operation of

[14] Here is an example: The enrollment of $t = 2012$, i.e., the school year 2011-2012, is determined in the recruitment season of 2011, in spring. At that time, students do not know the schools' accountability scores for the upcoming 2011-2012 school year starting 2011 in the summer. Therefore, a more appropriate measure for the state variable of performance level is the accountability score in 2011, which has been made public to schools and students since the start of the 2010-2011 school year.

[15] Potentially, one can digitize the Annual Five Year Plan document published by the local school districts to obtain all TPSs' capacity. However, the document does not provide the unique school ID number. Moreover, it does not use the same name as the school that appeared in NCES or Florida Master File data, making the exact merge across datasets impossible. Based on the data I can digitize and merge, it can be concluded that the number of classrooms in TPSs usually does not change over time.

Table 4. Full List of Variables with Measurement, Availability and Evolution Rule

Variable	Meaning	Measurment	Data Availability	Evolution of the Variable
Part A. Spatial State				
d_t	Local demographics	The proportion of each exclusive demographic groups by race and income and the age 5 14 population in year t, within 3 miles of the census tract where a school locates.		Markov, exogeneous
n_t	Local competitive pressure	The average accountability score in year t-1 of all the schools within 5 miles		Endogeneous
Part B. School State and Decisions				
k_t	Capacity	For charter schools, this is the number of classrooms in year t. For traditional schools, this is the largest enrollmentof observed divided by 22.		Endogenous
q_t	Performance level	For both types of schools, this is the accountability score in year t-1		Endogenous
hp_t	Designation	For charter schools, this is the designation status in year t. For TPS, this is zero in all situations.		Endogenous (independent of contemporaneous actions)
x_t	Increment in classroom	For charter schools, this is the first-difference of classrooms in t+1 and t. For TPSs, this is zero in all situations.		
z_t	Effort in performance	For both types of schools, this is the average teacher value-added score within a school in year t	2012-2019	
Part C. Other Variables				
ϵ_t	Unobserved heterogeneity	Random normal		I.I.D, exogeneous
E_t	Enrollment	For both types of schools, this is the total enrollment of K-8 grade		
Ψ_t	Operating cost of charter school	For charter schools, this is the total instructional expenditure	2007-2015	

charter schools after their entry. Additionally, the expansion in a charter school's early life cycle is predetermined and negotiated prior to entry, independent of post-entry factors such as designation and performance level. Therefore, including observations from this period would not be appropriate.

Lastly, I choose post-policy observations to estimate the structural model. As specified in the model, all schools are assumed to know the HP transition rule, and their belief about it remains unchanged. Therefore, the post-policy period is more suitable for estimating the model, particularly because the operation of the designation system is commonly known during this period and undergoes minimal changes. I therefore utilize the pre-policy data to evaluate the model's performance.

6.4 Empirical Specification and Identification

In the first step, I flexibly estimate the "offline" functions, the demand, operating cost, transitions, and policy functions, with appropriate functions of the state variables.

Demand, operating cost, and transitions To estimate enrollment, I regress the logarithm of enrollment on a set of functions, such as second-order polynomials, of the state variables. Similarly, for the operating cost of charter schools, I regress the logarithm of instructional cost on the same set of state variables and the logarithm of enrollment. Regarding the transition function of school performance, I experiment with flexible functional forms due to the complexity of the value-added formula. For the transition of the designation status, I exploit the empirical transitions of the conditional distribution of the future designation status across charter schools based on *only* contemporaneous performance and designation. This simplifies the modeling of the "2A1B" rule, which in reality requires three years of past performance, without losing too much accuracy. Lastly, I assume that a charter school does not lose the designation as long as it is designated[16].

Policy Functions As our model suggests and is supported by the real-world process of drafting new contracts and obtaining approval from the local school district, a fixed cost is associated with increasing the number of classrooms for instruction. In our structural estimation sample, approximately 70% of charter school observations remain inactive throughout the sample period, while the rest adjust their classroom counts. Thus, addressing the lumpiness in adjusting classroom counts is crucial when estimating the expansion policy functions.

To characterize the activity of adjusting capacity, I adopt the (S, s) rule following Attanasio (2000) and Ryan (2012). Ryan (2012) utilizes the same decision scheme to estimate cement manufacturers' capacity adjustment. In my context, the rule states that charter schools set a target, an upper band, and a lower band in each period based on a statistical rule to be estimated. According to the rule, a charter school increases classrooms to reach its target only when the number of classrooms falls below the lower band. It also decreases classrooms to reach its target when the number of classrooms exceeds the upper band. Following this rule, I employ Ordinary Least Squares (OLS) to estimate both the target and bands[17] using flexible functional forms of the state variables.

6.5 Identification of the Structural Parameters

The identification of the key structural parameters for both types of schools relies on the policy shock and the functional form assumptions imposed on $\Gamma(.)$. Firstly,

[16] As explained in the industry background, de-designation is rare in the sample. Furthermore, I rarely observe that eligible (i.e., those that pass the "2A1B" requirement) charter schools are not designated. The occurrence of these observations might reflect that they do not apply for the designation. Since they are rare, one convenient treatment is excluding them from the estimation sample.

[17] Ideally, there are two bands, upper and lower, to estimate. However, because shrinkage, i.e., the decrease in classrooms, is relatively less common compared to expansion, I assume that the shrinkage decision shares the same statistical relationship with the expansion decision and estimate the two bands by pooling all observations of expansion and shrinkage.

for charter schools, the cost of exerting v amount of value-added, namely γ_v, and the HP-related cost effects, namely γ_2 and γ_4, jointly govern the value-added decisions. These parameters can be separately identified by exploiting the policy shock. The early designated charter schools, e.g., those designated in 2012, do not need to adjust their value-added to secure future designation since they can never be de-designated. Hence, the difference in value-added choices between these schools and later-designated schools helps separate the HP-related cost effects and γ_v. Furthermore, the separability between γ_v, γ_2, and γ_4 facilitates identification. Specifically, γ_v can be identified by the variation in a school's performance in the following school year when its capacity remains unchanged between the two years as γ_2 and γ_4 only affect adjustment costs when charter schools expand. The identification of γ_v for TPSs follows a similar logic. Secondly, for charter schools, the fixed cost of expansion, γ_1, is identified by the frequency of charter schools choosing not to expand. Accordingly, γ_3 is identified by the variation in the consequent decisions following different magnitudes of expansions across or within schools. Naturally, the HP-related effects are identified by comparing the difference in expansion choices across charter schools or within those that experience a change in their HP status in the sample. The identification of the remaining parameters follows standard practices in the literature and is thus omitted here.

7 Structural Estimates

I run the structural estimation separately for charter and TPSs using charter and TPS observation respectively. Table (5) concludes the structural estimates for adjustment cost function $\Gamma(.)$. From the specification of schools' flow utility, a positive estimate indicates a cost. Notably, γ_2 is positive and precisely estimated, indicating that the HP designation decreases the fixed cost of initiating an expansion. The effect of HP designation on the variable cost of expansion, γ_4, is smaller in magnitude and not estimated with precision, as indicated by the ratio between its estimate and standard errors. Combined, these results align with the policy contents: The policy facilitates expansion ($\gamma_2 < 0$) for the HP charter schools but does not directly support expansion financially. The estimates of γ_v show that exerting value-added is costly for both charter schools and TPS. However, charter schools have lower costs. This might imply charter schools' higher efficiency in managing teachers in directing teaching goals to test scores. As expected, the fixed cost of expansion, γ_1, the variable cost of expansion in increasing one unit of a classroom, γ_3, are both larger in magnitude compared to the cost of value-added.

Table 5. Estimates of $\Gamma(.)$ and Standard Errors

	Adjustment Cost $\Gamma(.)$	
	TPS	Charter
Value-added Cost (γ_v)	1.8703	1.5692
	(0.2102)	(0.3704)
Fixed Cost of Expansion (γ_1)		5.3322
		(1.6011)
HP's Reward in Fixed Cost of Expansion (γ_2)		-6.7366
		(2.0406)
Variable Cost of Expansion (γ_3)		4.1145
		(0.3474)
HP's Reward in Variable Cost of Expansion (γ_4)		0.2869
		(0.4773)
HP's Variable Cost of Shrinkage (γ_5)		2.3266
		(0.2103)

Note: Standard errors (in parenthesis) are obtained by bootstrap that re-samples half of the initial states randomly for 100 draws with the same set of perturbed policy functions. All parameters are estimated assuming discount factor $\beta = 0.9$ and per-enrollment reimbursement $r = 0.08$, i.e., eight thousands per student. Hence all parameters are in hundreds of thousands of dollars.

8 Discussion

8.1 Counterfactual Analysis (In-Progress)

Removing the Designation System In this simulation, the objective is to investigate how the decisions of value-added and expansion would be across TPS and charter schools if the designation system were not in place , and how these changes impact the spatial distribution of schools' performance and capacity. To achieve this, the designation system and its associated cost effects are eliminated. Specifically, the HP transition rule is modified to make it impossible for schools to be designated, and the parameters γ_2 and γ_4 are set to zero. The focus of this simulation is primarily on understanding the changes in the average performance of schools through two channels. Firstly, charter schools lose the option value of increasing capacity at lower costs due to the absence of the HP designation system, which reduces their incentive to invest in costly (as γ_v shows) value-added to achieve high performance.

Secondly, TPSs may adjust their value-added decisions in response to changes in the performance of surrounding charter schools.

Including Value-added in the Designation Criteria This simulation explores the inclusion of high value-added as an additional criterion for HP designation, in addition to the existing criterion using performance level. Under this alternative policy, if a charter school surpasses a threshold value of value-added, it becomes eligible for designation. This simply means the transition function of the state HP is directly influenced by the amount of value-added achieved by a school. The aim of this simulation is to assess how the equality of good education resources across all schools can be improved by granting expansion eligibility to schools with high value-added, particularly those serving low socioeconomic status (SES) regions. The equality cannot be improved if modifying the designation criteria in such a way merely motivates charter schools serving low SES regions to expand. Therefore, whether this alternative policy improves equality is an empirical question. For example, the operating costs Ψ may vary across different demographic groups, such as the higher costs associated with educating low SES students, which could limit the potential expansion benefits.

Removing the Designation and Deregulating Capacity Expansion In this simulation, the HP designation system is eliminated, similar to the first counterfactual, while charter schools are provided with a cost reduction for expansion as if they were all designated as HP permanently. This implies that all charter schools would have fixed and variable expansion costs equivalent to those previously enjoyed by HP charter schools under the extant policy. The objective of this counterfactual scenario is to evaluate the extent to which TPS enrollment would be affected by the unconditional deregulation of capacity expansion in the charter sector. This simulation offers a perspective to assess both the potential "loss" (e.g., loss of public funds pumped to TPS) and "gain" (e.g., potential increase in effort by TPSs due to significant charter expansion) within the traditional sector. Consequently, policymakers with different objectives can make informed decisions based on their priorities.

8.2 Model Improvement: A Demand-model-based Measure n (In-Progress)

The state variable n, which represents the competitive pressure from neighboring schools, are currently measured by the average performance score of local schools.

While this measurement facilitates empirical implementation, it fails to account for capacity, relative distance, and relative performance of neighboring schools in a manner consistent with a proper school choice model. To address this limitation, a demand model is introduced, which enables the construction of a demand-model-based measure of neighboring competitive pressure while preserving the tractability of the dynamic model.

Similar to other demand models that consider heterogeneous agents (e.g., Berry et al., 1995), the proposed demand model captures students' preferences for school characteristics such as proximity, performance, HP designation, school type (charter or traditional), and unobserved school attributes. Students are differentiated based on observable local demographic variables. Students' school choices are summarized by the probability of choosing each school. These choices are then aggregated to predict school enrollment, which is compared to the actual enrollment of each school to estimate the demand parameters. To account for capacity constraints, students' preferences for schools are allowed to depend on class size, defined as enrollment per classroom. This treatment helps explain the observed low enrollment in constrained schools, as schools dislike larger class sizes, thereby correcting biased estimates of other school characteristics. The consideration of class size in students' preferences is inspired by Urquiola and Verhoogen (2008), who developed a model to study the sorting of Chilean schools under class-size caps. However, incorporating class size into students' preferences introduces correlations between class size and unobserved school attributes. To address this issue, an instrument for class size is constructed using a function of other observable attributes (excluding class size) of schools, following the approach of Bayer and Timmins (2007). The resulting demand model provides valuable insights into how enrollment responds to changes in performance and capacity, which are crucial elasticities for schools to consider in their supply-side decision-making. Notably, the existing literature on the industrial organization of the U.S. education market (Hastine et al., 2009; Ferreyra and Kosenok, 2018; Singleton, 2019; Dinerstein and Smith, 2021) has yet to explicitly account for such capacity constraints in their demand models.

With the estimated demand model, it becomes possible to reframe the predicted school enrollment from the demand model in a Logit form, incorporating all the state variables specified in the paper except for n. The remaining part of the Logit formula can be separated and used as a measure of n based on the estimated demand parameters. Although it is necessary to assume schools' beliefs regarding the evolution of the state variable n and re-estimate its transition accordingly, this approach is a standard practice in the empirical industrial organization literature on dynamic demand (Hendel and Nevo, 2006).

By employing the methodology described above, the current model's single-agent dynamic structure can be maintained, avoiding the complexity associated with simulating a dynamic game framework. Furthermore, a model-based representation of n with a suitable functional form is obtained.

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