The Effects of Centralized School Assignment on Public School Enrollment

by

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Submitted to the Department of Electrical Engineering and Computer Science
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ABSTRACT

An important benefit of modern school choice programs may be increased retention of students in large urban districts. Enrollment effects of choice frameworks are especially important today, as traditional public school enrollment as a share of total enrollment has fallen sharply since the pandemic. This paper asks whether and how the design of centralized assignment schemes, such as those used in numerous large urban districts, affects enrollment. Specifically, I focus on the question of how unified enrollment programs impact enrollment choice between traditional public schools, charter schools, and private schools. Using synthetic controls and event study models, this analysis suggests that the adoption of unified enrollment systems boosts charter enrollment as well as overall public school enrollment. At the same time, effect sizes vary across individual districts, and school choice policy should be mindful of the particular circumstances of each district.

Thesis supervisor: Joshua D. Angrist
Title: Ford Professor of Economics

Acknowledgments

This thesis represents the exploration into economics research that I've been hoping to take ever since I took my first economics class at Parkland High School over six years ago. In particular, education has been a passion of mine since the first moment I learned to line up my stuffed animals and prattle at them for hours about dinosaurs and planets. I'm so glad that I had the opportunity to complete this project, and it wouldn't have been possible without so many people in my life.

I would like to thank my thesis advisor, Prof. Josh Angrist, for his constant support and insightful direction. Your econometrics classes were fun, challenging, and rewarding, and gave me my first real glimpses into this field of scholarship. You've played an invaluable role in helping me narrow my research focus, guiding my analysis, and sharpening my writing. It is always an enjoyable and inspiring experience to work with you on any project, and especially on the most important project of my MIT career.

Thank you to my friends who motivated me just as much as they distracted me from finishing this thesis. I wouldn't have had nearly as much fun in the process without you.

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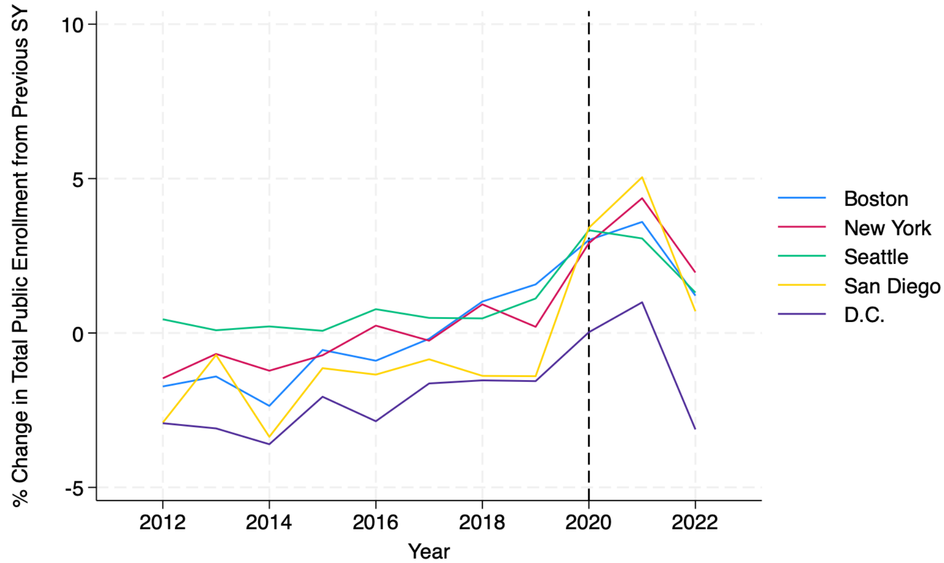
1 Introduction

In the aftermath of monumental court decisions mandating the integration of schools, many urban districts implemented or expanded school assignment schemes offering students district-wide choice. Boston, for instance, introduced controlled choice, in which parents could request enrollment in out-of-boundary schools, but each school was required to maintain racial balance in its acceptances [1]. These controlled choice programs laid the groundwork for later open enrollment policies of the late 1980s and 1990s, with Minnesota being the first state in 1988 to allow students to enroll in any public school district within the state with available seats [2]. The 1990s also saw the rise of charter schools, which have since been touted for their ability to deliver achievement gains, particularly to low-achieving and special needs students [3].

The earliest forms of intra-district open enrollment were typically characterized by idiosyncratic school-specific applications, each with distinct forms and deadlines. In addition, admissions were typically run by school principals. Selection could be opaque and arbitrary, and decentralized offers meant that multiple rounds of waitlist offers were necessary before enrollment could be finalized. To alleviate this frustrating uncertainty for both families and schools, Single Best Offer (SBO) systems were designed to algorithmically match each student to exactly one school assignment, maximizing welfare given individual preferences and school priority criteria. New York and Boston run centralized assignment (CA) SBO systems, integrating all district schools under one form, timeline, and assignment process. Magnet schools, exam schools, charter schools, and other alternative schools may still have their own separate application and decision processes. Some districts, including Denver and Newark, go further in unifying all types of schools under unified enrollment (UE) mechanisms. Though UE is generally considered to be a subclass of CA, for brevity I will use CA to refer to districts that fall under CA but cannot be classified as UE.

The post-pandemic years have seen sharp declines in public school enrollment, a trend

Figure 1.1: Post-pandemic drops in total public school enrollment in select districts



Note: This figure plots the percent changes in total public school enrollment numbers yearly from SY 2012-13 to SY 2022-23 for select large urban districts. The underlying data is taken from NCES Common Core of Data, reported at the school level and aggregated by district.

that can be seen in Figure 1.1. A survey of 33 states by Belsha, LeMee, Willingham, *et al.* [4] found that public K-12 enrollment has dropped by more than 500,000, or about 2% on average. This downswing is particularly pronounced in districts serving higher concentrations economically disadvantaged students [5]. These patterns can have dire effects on the communities in question, as public schools receive funding according to enrollment numbers. Cohen [6] partially attributes the post-pandemic decline in public school enrollment to the rise of school choice initiatives such as charter schools, which actually saw increased enrollment during the same time. This viewpoint casts expanded choice through CA and UE as taking resources away from the public sector and supports traditional neighborhood assignment as more equitable. On the other hand, Campos and Kearns [7] find that under the LA Zones of Choice UE system, studnet outcomes were significantly improved. This could be interpreted as a compelling argument in favor of UE, and it also motivates the question of whether UE can make public schools more attractive to families. Hoxby [8] additionally argues that the introduction of competition through choice programs motivates efficiency gains by public schools.

A large body of scholarship examines effects of choice on learning, but few analyses consider the enrollment consequences of choice in general and of centralized assignment schemes in particular.[1] This paper asks how the adoption of UE assignment processes affects public school enrollment by analyzing the staggered adoption of UE in five districts between 2011 and 2016. Of these districts, D.C. schools first implemented a CA system and later incorporated charters into the UE process used today, while the other districts (Camden, Denver, Newark, and NOLA) adopted UE without prior centralization. It is reasonable to predict that the streamlined application will increase charter school enrollment, while improving public school choice is likely to decrease private school enrollment.

As a benchmark, I begin with two-way fixed effects event study estimates of UE effects. Though these estimates show little evidence of substantial UE effects, the event study results also seem inconsistent with the key parallel trends assumption required for credible causal inference in this context. This identification failure motivates a more detailed synthetic control analysis. In addition to measuring the average effect of UE adoption on charter and private school enrollment shares across treated districts, I also examine district-specific effects. Average treatment effects are computed by constructing synthetic controls for each treated district and averaging effects in the same event time, a process described in more detail in Section 3.

Overall, UE appears to boost charter enrollment and reduce private enrollment. Estimates for individual districts are less precise but mostly point in the same direction. For instance, only in Denver and D.C. did UE adoption cause a significant change in private school enrollment, but in both cases the effect was negative. Notably, the districts where UE adoption increased charter enrollment did not also see a significant decrease in private

[1] Contemporary research generally suggests that school choice improves student achievement [9]. Angrist, Cohodes, Dynarski, *et al.* [10] additionally show that allowing students to choose charter schools boosts their standardized test scores and AP participation. Notably, Abdulkadiroğlu, Pathak, and Walters [11] find that a Louisiana voucher program that funds private school attendance for disadvantaged students reduces achievement.

school enrollment and vice versa. This implies that changes in public school enrollment are not driven primarily by students moving from private schools to charter schools.

2 Data and Descriptive Statistics

The treated (UE) districts used in this analysis are District of Columbia Public Schools, Newark Public Schools, Denver Public Schools, Camden City School District, and NOLA Public Schools. In unified enrollment districts as well as fully centralized districts, neighborhood schools may or may not be assigned by default. In Washington D.C., for instance, students are initially assigned based on home address, but all are free to fill out a My School DC lottery application to attend any out-of-boundary school. On the other hand, every family must fill out an application through Newark Enrolls in order to be placed in a Newark public school, though neighborhood students are prioritized.

Control districts are categorized into three distinct types: fully centralized (a CA system), partially centralized, and not centralized. A school district with full centralization has all of its traditional public district schools participating in one SBO assignment process. The fully centralized sample included New York City Public Schools, Boston Public Schools, Cambridge Public Schools, San Francisco Unified School District, Oakland Unified School District, Columbus City Schools, Minneapolis Public Schools, Charlotte-Mecklenberg Schools, and Winston-Salem/Forsyth County Schools.

The districts with no centralization that are included as controls are Anaheim Elementary School District/Anaheim Union High School District, Wake County (Raleigh) Public School System, Pittsburgh Public Schools, Jersey City Public Schools, Detroit Public Schools, and the School District of Philadelphia. These districts offer some opportunities for intradistrict choice, either in the form of open enrollment choice schools or in the form of transfers to out-of-boundary neighborhood schools. However, the process of applying to a school outside of a student's neighborhood zone is not centralized, so a student may receive multiple offers and may even have to fill out multiple applications if they want to apply to multiple alternative options.

If a district falls somewhere in between on the centralization spectrum, it is considered to be partially centralized. The partially centralized school districts used in this analysis were Baltimore City Public Schools and the San Diego Unified School District. These districts include some, but not all, of its public schools in an SBO assignment process. Further information on what partial centralization means for these districts can be found in Appendix A.

This classification of control districts into levels of centralization is necessary to reflect the pre-treatment characteristics of the treated districts. D.C. Public Schools implemented UE by building on an already existing CA system, so the synthetic control for D.C. is constructed using fully centralized and partially centralized control districts. For the other UE districts, intra-district choice was decentralized prior to UE adoption, so their synthetic controls use only partially centralized and non-centralized control districts.

For the districts of interest, enrollment data is publicly available from the National Center for Education Statistics (NCES). For public schools, the NCES Common Core of Data (CCD) includes annual enrollment numbers and demographic statistics aggregated at the school level. Private school data comes from the Private School Universe Survey (PSS), which provides a similar set of information and is conducted every two years. In order to avoid noise from pandemic related shocks in enrollment behavior, this analysis only includes data up to the 2019-20 school year.

Information on the intradistrict school choice policies for each district were compiled through an extensive review of existing literature and online resources. Using past reviews of school choice policy [12], [13] as a starting point, enrollment info pages on school district websites were used to identify districts which currently have assignment mechanisms in place. Open enrollment policy timelines were sources from a combination of academic literature, policy briefs, board meeting agendas, and even parent discussion boards. This information is documented in Appendix A. Based on these intervention start dates, summarized in Table A.1, this analysis begins in SY 2004-05 for charter enrollment analysis and in SY 2005-06 for private school enrollment analysis, since private school enrollment data is only available in odd years.

Table 2.1: Enrollment shares of school types by district (select years)

	District schools			**Charter schools**			**Private schools**		
	2005	**2011**	**2019**	**2005**	**2011**	**2019**	**2005**	**2011**	**2019**
Anaheim	.883	.871	.804	.020	.024	.061	.097	.105	.135
Baltimore	.740	.764	.752	.004	.027	.044	.256	.209	.203
Boston	.870	.847	.737	.072	.107	.210	.058	.046	.052
Cambridge	.545	.546	.641	.117	.165	.160	.337	.289	.199
Camden	.840	.792	.390	.103	.168	.565	.057	.040	.045
Charlotte	.873	.861	.855	.021	.043	.071	.107	.095	.074
Columbus	.689	.575	.613	.170	.290	.276	.141	.135	.111
Denver	.808	.795	.716	.052	.085	.190	.140	.120	.094
Detroit	.816	.642	.574	.157	.330	.405	.026	.028	.022
Jersey City	.750	.777	.720	.085	.099	.175	.165	.124	.105
Minneapolis	.751	.706	.682	.101	.161	.206	.148	.132	.112
New Orleans	.221	.127	.058	.136	.607	.738	.643	.267	.204
New York	.948	.925	.847	.010	.040	.117	.041	.035	.036
Newark	.833	.763	.640	.062	.164	.338	.105	.073	.022
Oakland	.816	.700	.612	.032	.157	.285	.152	.143	.103
Philadelphia	.700	.632	.573	.104	.204	.308	.196	.164	.119
Pittsburgh	.629	.599	.536	.036	.084	.157	.335	.316	.308
Raleigh	.894	.891	.875	.037	.040	.063	.069	.068	.061
San Diego	.846	.793	.747	.045	.106	.173	.109	.102	.080
San Francisco	.675	.680	.661	.016	.037	.106	.309	.283	.233
Washington	.633	.507	.498	.183	.330	.380	.183	.163	.123
Winston Salem	.915	.904	.910	.034	.034	.053	.050	.063	.038

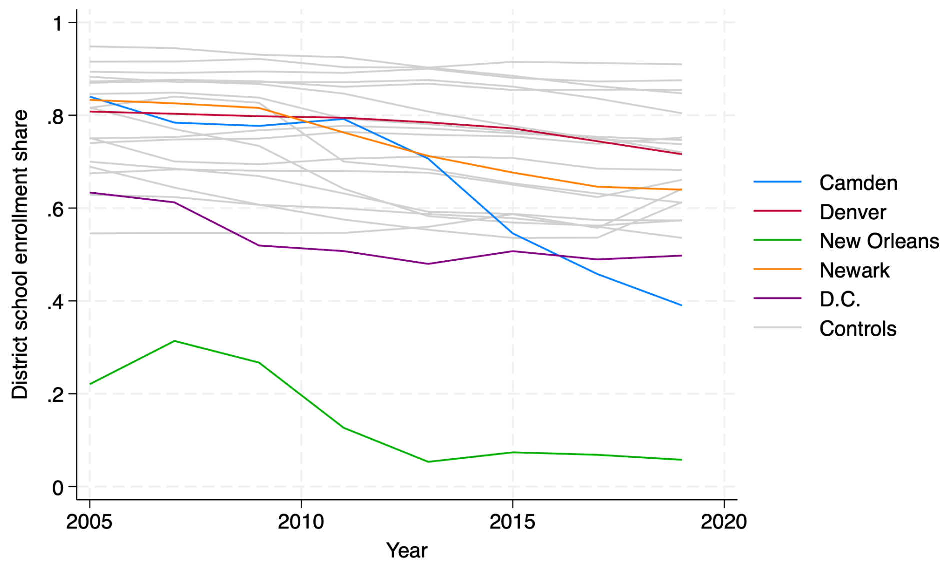
Note: Enrollment data from 5 UE districts (in bold) and 17 control districts is pulled from NCES at the school level and aggregated by district using school ID and location city. Enrollment for year t reports the number of enrolled students for the academic year starting in the fall of year t. Descriptive data is shown for the first year used in analysis, year of first treatment, and last year used in analysis. District and charter schools are classified using Agency Type reported by NCES Common Core of Data and private schools are taken from NCES Private School Survey.

Public school data was aggregated by district for this analysis, which required identification of the schools within each district. In the case of some large urban districts, such as the San Francisco Unified School District, it is sufficient to filter by location city. In other cases, it was necessary to use the district's NCES-assigned ID number or state-assigned ID number for differentiation. For example, the New York City Public Schools encompasses the five boroughs of New York City, with some schools listed under more granular location cities such as Astoria, Flushing, Jackson Heights, etc. Other cities may be home to more than one school district, not all of which have the same centralization policies. Columbus City Schools in Ohio has an open-enrollment system which allows a student to apply to three schools of their choice, but the nearby South-Western City School District assigns students by home address only. Charter and private schools that could be considered alternatives for the district schools were determined to be those schools registered in the same city as the district of interest for at least one of the years between 2003 and 2019. For districts that spanned multiple reported location cities, charter and private schools in each of the location cities that appeared in the district are included. Appendix A provides more details on this identification process.

2.1 Summary Statistics

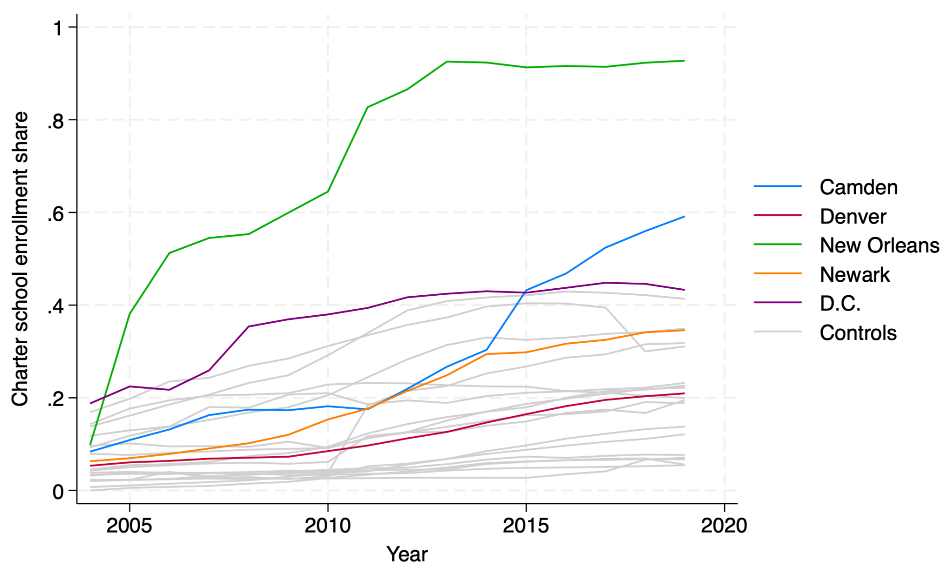
Table 2.1 reports the proportion of students in each district enrolled in traditional district schools, charter schools, and private schools for select years that cover the timespan of the data collected. Only odd years are reported due to the limitations of the private school enrollment dataset. The districts which adopted UE during this time period are bolded. Figure 2.1, Figure 2.2, and Figure 2.3 plot these trajectories over the full time period, with treated districts highlighted. It is evident from the trends that two districts, D.C. and New Orleans, had high proportions of students enrolled in charter schools in the years before treatment. Methods used to adjust for these extreme values are discussed in Chapter 3, including leaving these districts out of the pooled charter enrollment analysis. Also note

Figure 2.1: Traditional district school enrollment share by district



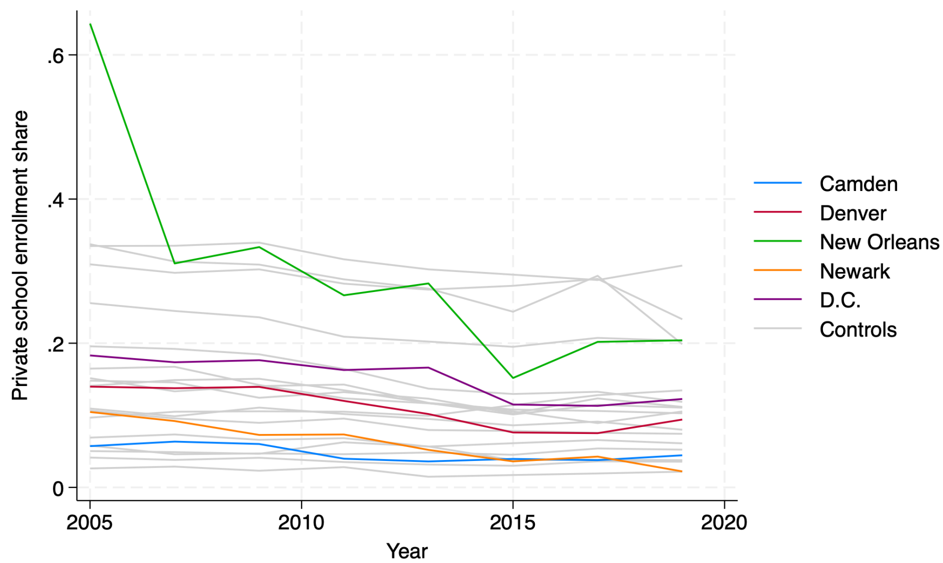
Note: Enrollment data from 5 UE districts and 17 control districts is pulled from NCES Common Core of Data at the school level and aggregated by district. Enrollment for year t reports the number of enrolled students for the academic year starting in the fall of year t. Traditional district schools are those with Agency Type "Regular local school district not part of a supervisory union" or "Local school district that is part of supervisory union" in NCES dataset.

Figure 2.2: Charter enrollment share by district



Note: Enrollment data from 5 UE districts and 17 control districts is pulled from NCES Common Core of Data at the school level and aggregated by district using school ID and location city. Enrollment for year t reports the number of enrolled students for the academic year starting in the fall of year t. Charter schools are those with Agency Type "Charter school agency" in NCES dataset.

Figure 2.3: Private school enrollment share by district



Note: Enrollment data from 5 UE districts and 17 control districts is pulled from the NCES Private School Survey at the school level and aggregated by district using location city. Enrollment for year t reports the number of enrolled students for the academic year starting in the fall of year t.

that the charter enrollment share numbers differ slightly because Table 2.1 reports charter enrollment share as a proportion of all students while Figure 2.2 reports charter enrollment share as a proportion of public school students. This analysis uses the latter for charter enrollment share estimates. Finally, note that the spike in private school enrollment for New Orleans in 2005 is likely due to shocks from Hurricane Katrina. This year is excluded in later analysis for New Orleans.

3 UE Effects

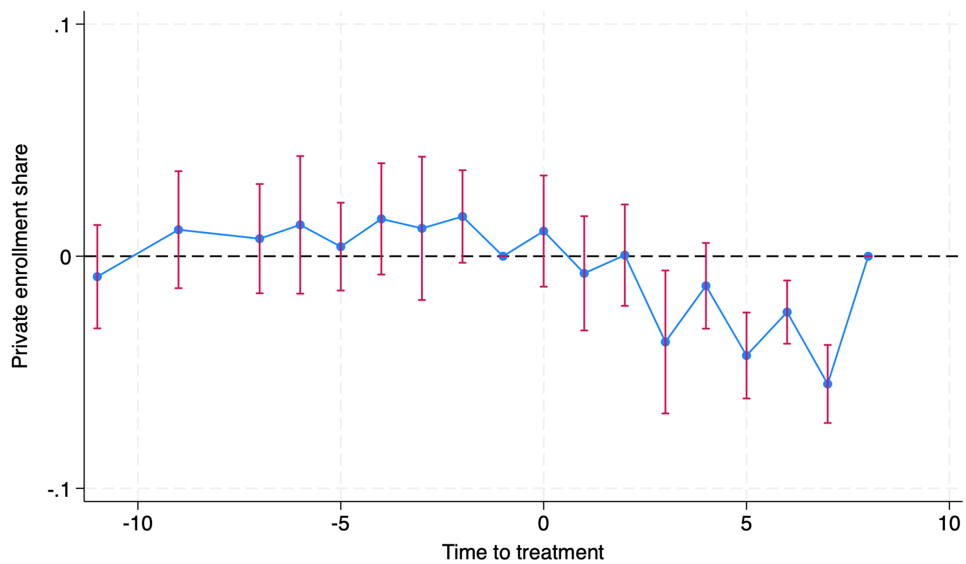
3.1 Event Study Estimates

Event study estimates generalize the differences-in-differences framework to allow for time-varying effects anchored at the point of a policy change. I begin with an event study analysis that compares changes in UE reforming districts with districts that have not (yet) adopted UE. Causal effects in the setup are identified by the assumption of parallel trends. Specifically, this critical assumption requires that in the absence of treatment, the difference between the treated group and the untreated group is constant over time. For multiple treated groups with staggered adoption times, an event study can be performed to test the validity of the assumption.

Figure 3.1 suggests UE reduces private school enrollment significantly, by almost 5% in five to seven years following treatment. Importantly, the estimated leads plotted in this figure show little evidence of diverging trends between reforming and non-reforming districts prior to the intervention. None of the pre-treatment lags have significantly non-zero effects on the outcome variable, and several of the post-treatment periods show significant negative effects. This implies that UE adoption did bring students back into the public school system.

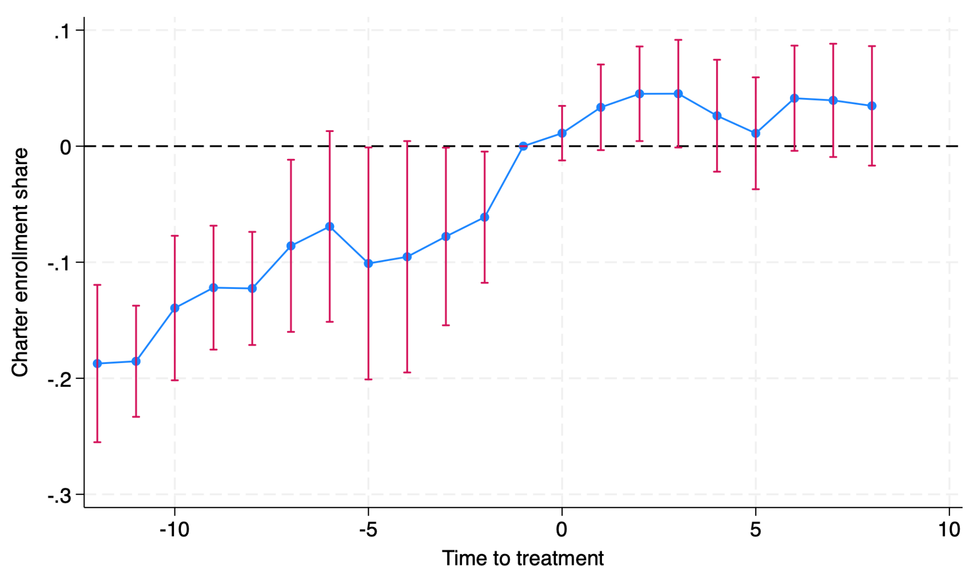
Taken at face value, the estimates in Figure 3.2 suggest that UE had little effect on charter enrollment. In contrast with the private school effects shown in Figure 3.1, however, the event study estimates of charter school effects show statistically significant leads. Thus it appears that two-way fixed effects models fail to identify causal UE effects on charter enrollment due to significant differences between treatment and control districts prior to treatment. This result motivates the use of synthetic controls in further analysis.

Figure 3.1: Event study estimates of effect of UE adoption on private school enrollment



Note: This figure plots the estimated coefficients on lags and leads of UE adoption in an event study regression. The regression controls for district and time fixed effects. 95% confidence intervals are displayed, calculated from standard errors clustered at the district level. Enrollment data prior to 2007 is excluded for New Orleans.

Figure 3.2: Event study estimates of effect of UE adoption on charter school enrollment



Note: This figure plots the estimated coefficients on lags and leads of UE adoption in an event study regression. The regression controls for district and time fixed effects. 95% confidence intervals are displayed, calculated from standard errors clustered at the district level. Charter enrollment share is calculated as a proportion of total public school enrollment. Enrollment data prior to 2007 is excluded for New Orleans.

3.2 Synthetic Control Estimates

In cases where the parallel trends assumption does not hold, Abadie [14] describes a way to build a synthetic control using a weighted average of multiple untreated units (known as the donor pool). The weights are algorithmically fitted to match the pre-treatment trends of the outcome variable and other covariates, allowing the resulting synthetic control to provide a plausible counterfactual for the treated group. For multiple treated units with staggered adoption times, treatment effects are calculated using synthetic controls for each unit individually, after which effects are averaged by event time. This methodology, used by Cavallo, Galiani, Noy, *et al.* [15] and Ben-Michael, Feller, Rothstein, *et al.* [16], is similar to how treated groups are pooled in event study models.

Given the availability of multiple untreated groups similar to the treated group, the parallel trends assumption can be relaxed and replaced by the requirement of close pre-treatment fit. Moreover, the construction of the synthetic control via optimization for weights to fit chosen covariates is a more formalized and data driven process than the usually ad hoc choice of the control group(s) for a differences-in-differences comparison. Another perk of using synthetic controls is the transparency of the control fit and the synthesized counterfactual. The nonzero weights used to construct the synthetic control have a meaningful interpretation, and external information can be employed to validate the estimated counterfactual or to estimate the direction of potential bias.

3.3 Model Setup

Given data for districts $j = 1, 2, \ldots, J$ (denote district 1 to be the treated district), the goal is to estimate the effect of the treatment on the treated:

$$\tau_{1t} = Y_{1t}^1 - Y_{1t}^0$$

in the post-intervention period $T_0 + t$, where T_0 is the time of treatment, in this case UE adoption. Note that this model allows the estimated treatment effect to vary over time. Y_{1t}^0 is defined to be the potential outcome without intervention. To reproduce this potential outcome, I estimate the weighted average

$$\hat{Y}_{1t}^0 = \sum_{j=2}^{J} w_j Y_{jt}$$

and the treatment effect

$$\hat{\tau}_{1t} = Y_{1t} - \hat{Y}_{1t}^0.$$

In this application, I analyze the effect of UE adoption on both charter enrollment share and private school enrollment share, so I will produce two different sets of estimates using those two outcome variables.

To determine donor pool weighting, the goal is to choose $w_2, \ldots, w_J$ so that the resulting synthetic control best resembles pre-intervention values for covariates of the treated unit. To do this, I estimate $W = (w_2^*, \ldots, w_J^*)$ that minimizes RMSE

$$||X_1 - X_0 W|| = \left(\sum_{h=1}^{k} v_h (X_{h1} - w_2 X_{h2} - \cdots - w_J X_{hJ})^2 \right)^{1/2},$$

where $w_2, \ldots, w_J$ are nonnegative and sum to 1. Here, X_1 contains the pre-treatment outcome variable trends as well as the chosen covariates, and $X_0 W$ contains those values for the synthetic control. The estimated treatment effect is

$$\hat{\tau}_{1t} = Y_{1t} - \sum_{j=2}^{J} w_j^* Y_{jt}.$$

Now assume there are G treated districts. The estimated average effect of UE adoption for the G treated districts is then

$$\hat{\tau}_t = \frac{1}{G} \sum_{g=1}^{G} \hat{\tau}_{gt}.$$

3.4 Inference

The inference procedure for synthetic controls builds on the idea of a placebo test. "Placebo effects" are estimated by iteratively reassigning the control units to be the treated unit. A separate synthetic control is fitted for each of the fake treated units, excluding the actual treated unit from the donor pool. A permutation distribution is then constructed by pooling these placebo effects with the estimated effect on the real treated unit, and the estimated treatment effect is considered significant if its magnitude is large relative to the placebo effects. The p-value is then equal to the number of placebo effects that exceeds the main estimated effect in magnitude:

$$p_{1t} = \frac{1}{J} \sum_{j \neq 1} \mathbb{1} \left(|\hat{\alpha}_{jt}| \geq |\hat{\alpha}_{1t}| \right)$$

where $\hat{\alpha}_{jt}$ is the estimated effect on unit j for period $T_0 + t$. However, this p-value does not take into account pre-treatment fit of each unit. A control unit may have a larger effect by magnitude than the treated unit, but also a worse synthetic control fit, or vice versa. To take this into account, a standardized p-value can be calculated by dividing each treatment effect by pre-treatment match quality, defined by the pre-treatment RMSPE. The standardized effect can be expressed as

$$r_{jt} = \frac{\hat{\alpha}_{jt}}{RMSPE_j(1, T_0)}.$$

The standardized p-value is then

$$p_{1t} = \frac{1}{J} \sum_{j \neq 1} \mathbb{1} \left(|r_{jt}| \geq |r_{1t}| \right).$$

To conduct inference for the average treatment effect, a permutation distribution is constructed using average placebo effects. For each treated district g, all placebo effects are calculated from the $J - 1$ control districts. Each averaged placebo effect is computed by

Table 3.1: Average effect of Unified Enrollment on charter and private school enrollment share, synthetic control estimates and p-values

	Charter			Private		
t	Effect	p-value	Std. p-val	Effect	p-value	Std. p-val
0	.0500	.000	.000			
1	.0648	.000	.000	-.0168	.000	.000
2	.0800	.000	.000			
3	.0917	.000	.000	-.0421	.000	.000
4	.1028	.000	.000			

Note: t denotes the number of years since UE implemented. p-values and p-values standardized by pre-treatment match quality are reported. Due to suspected anticipation effects, UE intervention is backdated by one year, as recommended by Abadie [14]. D.C. and New Orleans are excluded from charter enrollment analysis here due to extreme values. D.C. uses fully centralized and partially centralized control groups as the donor pool for the synthetic control. All other treated groups use partially centralized and non-centralized control groups. Enrollment data prior to 2007 is excluded for New Orleans.

choosing one placebo effect corresponding to each treated district and averaging over the G chosen placebo effects. At each lead t, the $N_{PL} = G(J-1)$ possible averaged placebo effects make up the permutation distribution and the p-value is given by

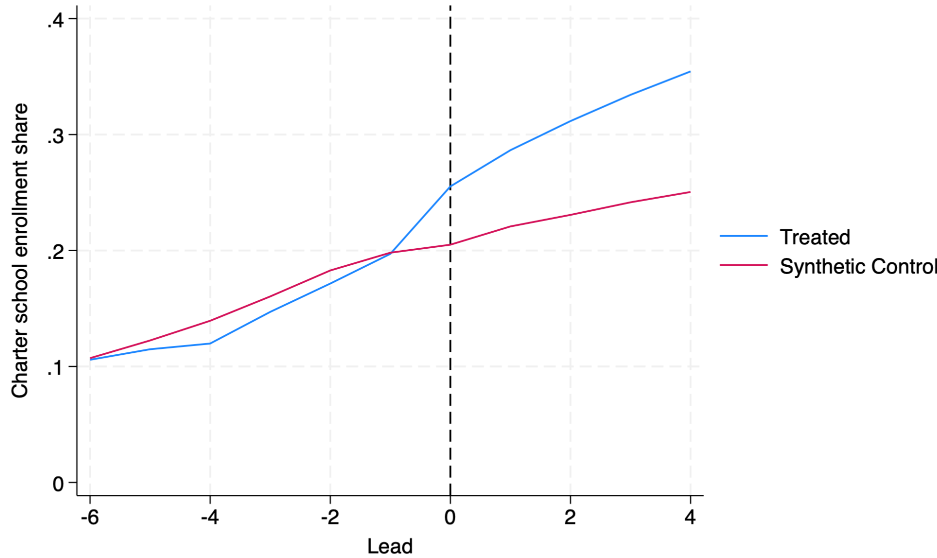
$$p_t = \frac{1}{N_{PL}} \sum_{n=1}^{N_{PL}} \mathbb{1}\left(|\hat{\tau}_t^{PL_n}| < |\hat{\tau}_t|\right).$$

This method of constructing a permutation distribution accounts for the smoothing effects of averaging treatment effects across treated districts. The standardized version of this pooled p-value is computed analogously to the single treated unit case.

3.5 Synthetic Control Estimates

Results from synthetic control analysis reveal that UE adoption raises charter school enrollment share as well as overall public school enrollment share. Figure 3.3 shows the evolution of charter enrollment share in UE adopting districts and corresponding synthetic control districts over time, averaged for each lead and lag. In the years after UE adoption, the lines diverge, and charter enrollment share has risen by 10% by the fourth year after treatment, as reported in Table 3.1. As seen in Figure 3.4, there is a dip in private school enrollment

Figure 3.3: Synthetic control plot of charter school enrollment



Note: This figure plots charter school enrollment share as a fraction of total public school enrollment. Lead denotes the time since UE implemented. Due to suspected anticipation effects, UE intervention is backdated by one year, as recommended by Abadie [14]. D.C. and New Orleans are excluded from this analysis due to extreme values. All included treatment groups use partially centralized and non-centralized control groups as the donor pool for the synthetic control. Enrollment data prior to 2007 is excluded for New Orleans.

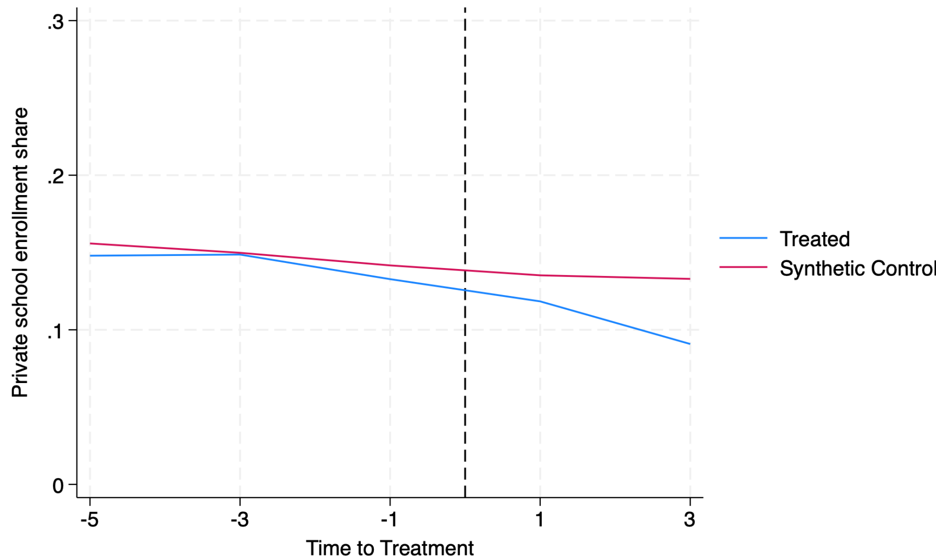
share following UE adoption, reaching 4% by the third year after treatment.

As shown in Table 3.3 and Table 3.4 as well as in Figure 2.2, D.C. and NOLA had unusually high pre-treatment charter enrollment compared to the other districts used in this analysis. This presents a challenge in pooled synthetic control analysis, as it is impossible to construct a weighted average of the donor pool districts which replicate these pre-treatment trends. Thus, the pooled analysis of charter enrollment effects leave out the D.C. and NOLA school districts, and individual analysis of these districts require applying a shift to the dependent variable, as described in Section 3.7 and Section 3.9.

Though average treatment effects are statistically significant, it is still not clear from this pooled analysis whether the increase in public school enrollment is driven by students substituting charter schools for private schools. Examining the synthetic control estimates for individual districts separately suggests that this is not the case.

Indeed, synthetic control estimates reported in Table 3.2 indicate that the adoption

Figure 3.4: Synthetic control plot of private school enrollment



Note: This figure plots charter school enrollment share as a fraction of total public school enrollment. Lead denotes the time since UE implemented. D.C. uses fully centralized and partially centralized control groups as the donor pool for the synthetic control. All other treated groups use partially centralized and non-centralized control groups. Enrollment data prior to 2007 is excluded for New Orleans.

of UE did not affect every district in the same way. While most districts saw negative, statistically insignificant effects of UE on charter school enrollment share, Camden's charter school enrollment saw a statistically significant increase in charter school enrollment share. On the other hand, the introduction of UE in several districts seemed to result in a modest drop in private school enrollment share. In the following sections, I discuss each district's estimation results in context of their UE adoption.

3.6 Denver

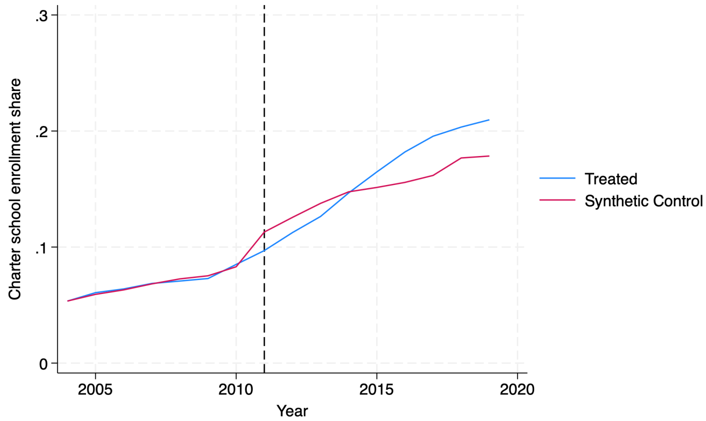
Denver Public Schools (DPS) was the first of the major urban districts in the country to unify school enrollment across its district and charter schools. DPS was perhaps uniquely poised to enact this reform early, as Denver charter schools are directly authorized by DPS instead of a statewide education oversight entity [17]. The change was pushed by community members who criticized the convoluted existing choice processes, which involved sifting through over

Table 3.2: Effect of Unified Enrollment on charter and private school enrollment share, synthetic control estimates and p-values

		Charter			Private		
	t	Effect	p-value	Std. p-val	Effect	p-value	Std. p-val
Camden	0	.1558	.000	.125			
	1	.2038	.000	.125	.0021	.833	.833
	2	.2341	.000	.250			
	3	.2592	.000	.250	.0031	.833	.833
Denver	0	-.0160	.286	.143	-.0106	.200	.000
	1	-.0131	.571	.286			
	2	-.0113	.714	.429	-.0204	.000	.000
	3	-.0009	.857	.857			
	4	.0134	.714	.429	-.0443	.000	.000
	5	.0262	.429	.286			
	6	.0338	.286	.286	-.0496	.000	.000
	7	.0266	.429	.429			
	8	.0312	.286	.429	-.0307	.200	.000
New Orleans*	0	-.0297	.750	.250			
	1	-.0174	1.000	1.000	-.0091	.000	.333
	2	-.0845	.750	.625			
	3	-.1328	.500	.375	-.0223	.333	.333
	4	-.2624	.000	.250			
	5	-.3549	.000	.125	-.0108	.667	.833
	6	-.5642	.000	.250			
	7	-.5807	.000	.250	-.0383	.333	.333
Newark	0	.0592	.000	.000			
	1	.0546	.000	.125	-.0131	.500	.500
	2	.0559	.000	.125			
	3	.0546	.000	.125	-.0083	.833	.100
	4	.0697	.000	.250			
	5	.0701	.000	.250	-.0287	.333	.667
D.C.*	0	-.1604	.400	.100			
	1	-.2378	.300	.200	-.0486	.000	.000
	2	-.1879	.400	.300			
	3	-.2085	.400	.400	-.0596	.000	.000
	4	-.2399	.500	.400			
	5	-.2715	.500	.300	-.0210	.222	.000

Note: t denotes the number of years since UE implemented. p-values and p-values standardized by pre-treatment match quality are reported. Charter enrollment shares are calculated as a fraction of total public school enrollment. Private enrollment effects are only reported for alternating years because PSS data is only collected for odd years.
*For New Orleans and D.C., the outcome variable used for charter effects is adjusted due to extreme values relative to control units. Instead of charter enrollment share, the log difference in charter enrollment share from pre-treatment means is used. The pre-treatment period for D.C. was 2004-2013, and for New Orleans it was 2006-2011.

Figure 3.5: Synthetic control weights and plot for Denver charter school enrollment



District	**Weight**
Anaheim	.267
Baltimore	.032
Detroit	0
Jersey City	0
Philadelphia	.237
Pittsburgh	0
Raleigh	.103
San Diego	.361

Note: This figure plots charter school enrollment share as a fraction of total public school enrollment. The blue line represents the Denver school district, and the red line represents the synthetic control districts. The table on the right reports the weights assigned to each district in the donor pool, which includes partially centralized and non-centralized districts.

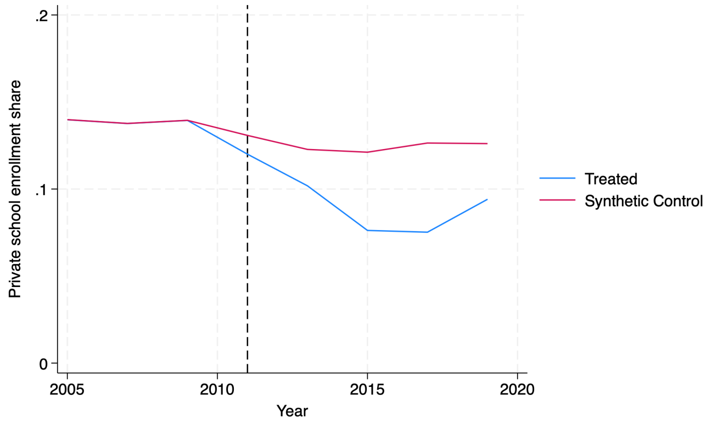
60 individual forms and deadlines for district schools and almost 30 more for the city's charters [13].

The DPS SchoolChoice application is optional, as students are assigned to their neighborhood school by default. For those who would like to attend a different school, the application allows a student to submit five ranked choices, choosing from traditional district, innovation, magnet, and charter schools in one streamlined match. The DPS system is often lauded as an example of the success of UE. In 2016, over 80 percent of students in each grade level were matched to their top choice school [13], though there is criticism that the amount of choice realistically available to families is somewhat inhibited by the limitations of the city's school bus system [18].

The adoption of UE in Denver did not significantly affect charter enrollment. From Figure 3.5 and Figure 3.6 we can see that the resulting synthetic control closely matches the pre-treatment trends of the treated district. The p-values reported in Table 3.2 imply that students applying to charter schools after the unification of the enrollment processes would have applied even with the more complicated system.

On the other hand, the adoption of UE reduced the share of students attending private

Figure 3.6: Synthetic control weights and plot for Denver private school enrollment



District	Weight
Anaheim	.204
Baltimore	.068
Detroit	.051
Jersey City	.062
Philadelphia	0
Pittsburgh	.127
Raleigh	.118
San Diego	.37

Note: This figure plots private school enrollment share. The blue line represents the Denver school district, and the red line represents the synthetic control districts. The table on the right reports the weights assigned to each district in the donor pool, which includes partially centralized and non-centralized districts.

schools in Denver, as evidenced by the private school enrollment effects estimated in Table 3.2 as well as the observable trends in Figure 3.6. This effect is also significant, based on the p-values in most time periods and the p-values standardized by pre-treatment fit in all periods. The size of the effect is as large as 5% six years after the start of UE, which is notable since the private school enrollment share prior to treatment was only about 14%. Figure 3.7 again demonstrates the close fit of DPS pre-treatment trends to the synthetic control contrasted with the negative trend post-treatment which is more extreme than any of the placebo comparisons.

3.7 New Orleans

In the aftermath of Hurricane Katrina in 2005, the New Orleans public school system (NOLA-PS) underwent dramatic reforms. One consequence of the disaster was that many families faced uncertain housing situations, and as a result they were no longer placed in a neighborhood school by default. This forced NOLA-PS families into school choice via decentralized mechanisms in which individual schools determined their own admission procedures, which raised equity concerns as well as suspicion regarding possible discrimination by school leaders

Figure 3.7: Effects plot for Denver and control units

Note: This figure plots the post-treatment effects of UE adoption on private school enrollment share for the Denver school district. The gray lines display the placebo effects computed for the donor pool districts.

[19].

The state of Louisiana also established the Recovery School District (RSD) in the fall of 2005, taking over all schools operated by Orleans Parish School Board (OPSB) that were deemed "underperforming" prior to Katrina. RSD quickly converted most of these to charter schools and instated open enrollment policies and lottery-based admissions processes at each school. Noting the difficulty of navigating the decentralized application system in NOLA-PS, RSD gradually worked to simplify enrollment throughout the district, starting with a common application form for RSD schools in 2008 [20]. Student assignment was later unified in 2012, with the creation of the OneApp system and a central Office of Enrollment [21].

OneApp allows families to rank up to eight schools, with a family link option that attempts to place siblings together. When entering a new school, all families are required to submit an application, even if they want to attend their neighborhood zoned school. Generally, schools prioritize neighborhood students for half of their seats, but NOLA-PS also

Table 3.3: Pre-treatment averages of New Orleans and control units

District	Average charter share
Anaheim	0.0255
Baltimore	0.0187
Detroit	0.2508
Jersey City	0.0993
New Orleans	**0.6137**
Philadelphia	0.1813
Pittsburgh	0.0819
Raleigh	0.0416
San Diego	0.0683

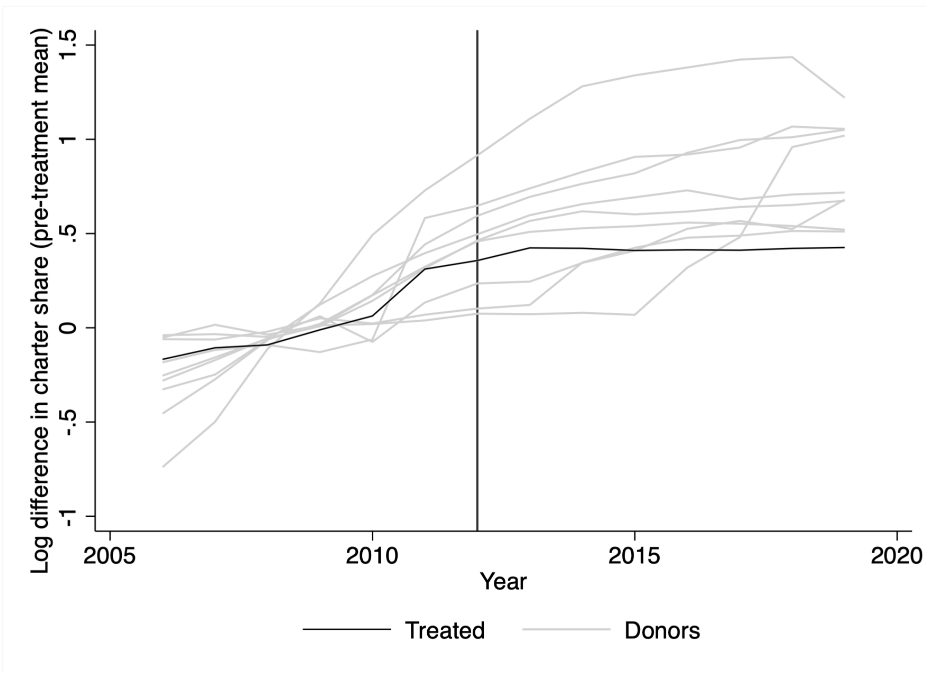
Note: This table displays the average charter share in the NOLA district and control districts prior to UE adoption in NOLA-PS in 2012. Charter enrollment share as a fraction of total public school enrollment is averaged across the years from 2006 to 2012.

buses almost all students living over a mile away from their school [13]. All schools under RSD and those directly controlled by OPSB were added to OneApp, though several charter schools held out for some time. Starting in 2013, charters were forced to participate in the UE system under OneApp in order to renew their contracts, and the last of the charters signed before OneApp expired by 2022 [21].

NOLA-PS differs from the donor pool districts in that its charter sector accounts for a particularly substantial portion of total student enrollment, in large part due to reforms after Katrina. As shown in Table 3.3, the average charter enrollment share in NOLA-PS in the pre-treatment period was over 47%, while the largest share among the other districts was 21%, with most districts sitting below 10%. This made it impossible for the synthetic control weight optimization to match the NOLA-PS pre-treatment trends.

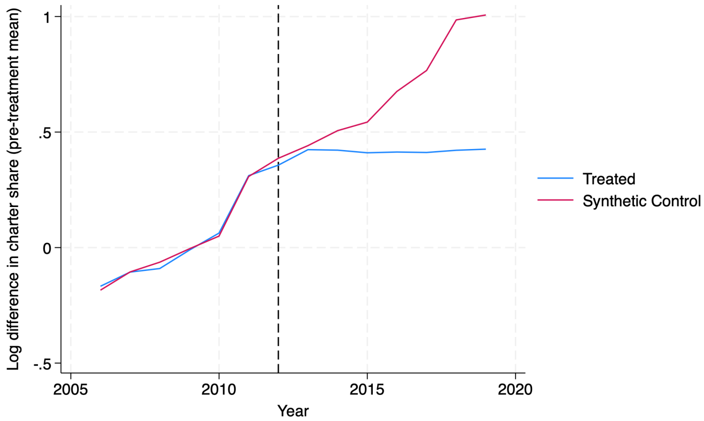
To remedy this, as noted in Table 3.2, the dependent variable was adjusted to be the difference in log charter enrollment shares relative to pre-treatment mean. A similar approach is suggested by Ferman and Pinto [22] when the treated unit is extreme in the outcome variable values before treatment. The adjusted trajectories can be seen in Figure 3.8. These new values were used to build the synthetic control as displayed in Figure 3.9. Another adjustment was to only use data starting from 2006 due to shocks from Hurricane Katrina

Figure 3.8: Outcome paths for New Orleans and control units using adjusted outcome variable



Note: This figure shows the trajectories of the NOLA school district and donor pool districts using the adjusted outcome variable. The log of pre-treatment average charter enrollment share for each district is subtracted from the log charter enrollment share in each period.

Figure 3.9: Synthetic control weights and plot for New Orleans charter school enrollment



District	Weight
Anaheim	.401
Baltimore	.111
Detroit	0
Jersey City	.136
Philadelphia	0
Pittsburgh	.081
Raleigh	0
San Diego	.270

Note: This figure plots charter school enrollment share as a fraction of total public school enrollment. The blue line represents the NOLA school district, and the red line represents the synthetic control districts. The table on the right reports the weights assigned to each district in the donor pool, which includes partially centralized and non-centralized districts.

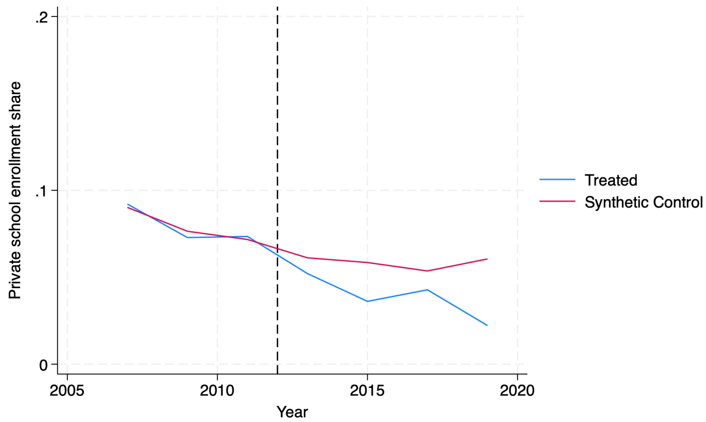
and the establishment of RSD in 2005.

Based on the Figure 3.9 as well as the reported estimates in Table 3.2, the charter enrollment share grew less at NOLA-PS relative to pre-treatment outcomes than would be predicted by the trends seen at other schools past year 4 of UE. We can observe from the graph that the synthetic control is able to closely replicate the pre-treatment trends of the adjusted outcome variable for the treated group. This result should be interpreted with caution, however, as the NOLA-PS charter enrollment share grew to more than 90% in 2013. It then makes sense that charter enrollment share growth slowed for NOLA-PS after that, as they did not have as much room to expand. There is no significant difference in private school enrollment share between the treated and control districts.

3.8 Newark

During a 22-year state takeover that lasted until 2017, Newark Public Schools (NPS) underwent a series of improvement efforts. One of these reforms was a district restructuring plan called "One Newark", which included Newark Enrolls, a new system which would unify the district's 90 traditional, magnet, charter, and special education schools under a single SBO

Figure 3.10: Synthetic control weights and plot for New Orleans private school enrollment



District	**Weight**
Anaheim	0
Baltimore	0
Detroit	.56
Jersey City	.44
Philadelphia	0
Pittsburgh	0
Raleigh	0
San Diego	0

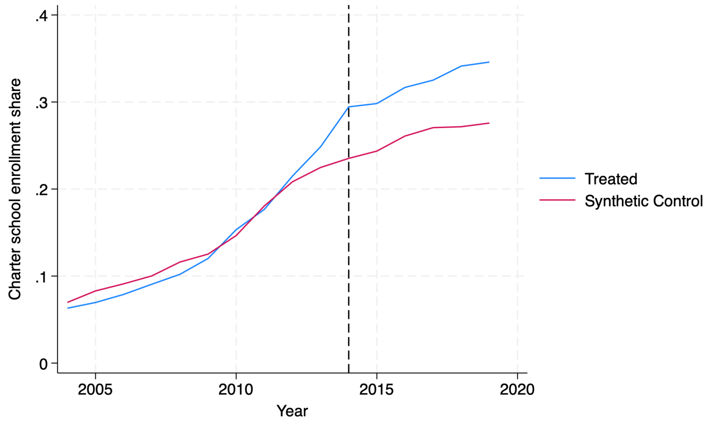
Note: This figure plots private school enrollment share. The blue line represents the NOLA school district, and the red line represents the synthetic control districts. The table on the right reports the weights assigned to each district in the donor pool, which includes partially centralized and non-centralized districts.

process [13].

In the 1990s and 2000s, Newark's magnet and charter schools ran their own enrollment processes independently of each other and of the district, sometimes forcing families to line up in front of administration buildings before sunrise in hopes of claiming a seat at a high demand school. Parents with fewer resources were often unable to juggle multiple applications and deadlines, manipulate work schedules to get in line for a school, and utilize other tricks to "game the system". Families who were well-connected, on the other hand, could often get into sought-after schools through backdoor methods [23]. These conditions raised an array of equity concerns and resulted in severe distributive inequality.

In 2012, NPS launched a centralized application for its magnet schools. In 2013, the application expanded to include all NPS district schools. The next year, Newark Enrolls was created, allowing students to apply to almost any school in the district under one application and selection process. Like New Orleans, it took some time for a few holdout charter schools to join [23]. When entering a new school, all families must submit an application, even if they would like to attend their neighborhood school. Each student can rank up to eight schools, and sibling and neighborhood priority both apply in the lottery process. Students

Figure 3.11: Synthetic control weights and plot for Newark charter school enrollment



District	Weight
Anaheim	0
Baltimore	0
Detroit	.265
Jersey City	0
Philadelphia	0
Pittsburgh	.735
Raleigh	0
San Diego	0

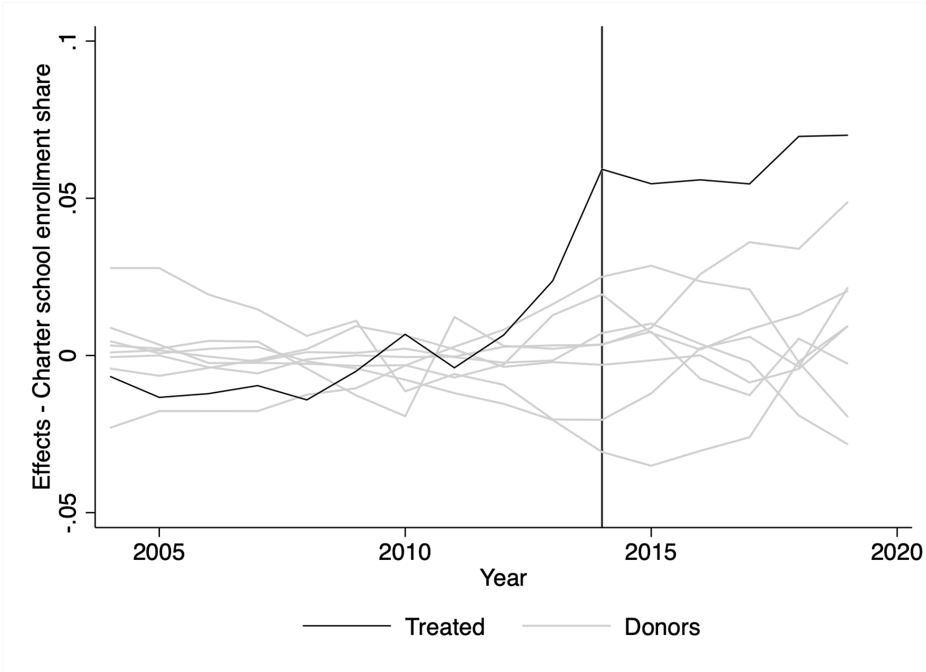
Note: This figure plots charter school enrollment share as a fraction of total public school enrollment. The blue line represents the Newark school district, and the red line represents the synthetic control districts. The table on the right reports the weights assigned to each district in the donor pool, which includes partially centralized and non-centralized districts.

who live more than two miles away from their assigned school are bused by the district [13]. Additionally, magnet schools give weight to metrics such as grades, attendance, and test scores, and a certain proportion of seats are set aside at each school for special education and free lunch eligible students. Newark Enrolls also provides support to families at each step of the process, including awareness campaigns before the enrollment period begins and guidance for unhappy families after the enrollment period ends [23].

In Table 3.2, the estimates indicate that the UE system moderately increased charter enrollment in Newark. We can see that this 5 to 7 percentage point effect is statistically significant, but not when adjusted by pre-treatment match quality.

As seen in Figure 3.12, the effects on Newark post-treatment are largest out of any unit, but some units have better pre-treatment fit. However, the pre-treatment effects for Newark do hover extremely close to zero before diverging in the post period. Additionally, both the synthetic control trajectory plot and the effects plot demonstrate that the trends for NPS begin to diverge visibly from the synthetic control trajectory around 2012, which corresponds to the beginnings of centralized enrollment processes in NPS. The gap between the synthetic control and treated trajectories in Figure 3.11 seems to widen from 2012 to 2014, at which

Figure 3.12: Effects plot for Newark and control units



Note: This figure plots the post-treatment effects of UE adoption on charter school enrollment share for the Newark school district. The gray lines display the placebo effects computed for the donor pool districts.

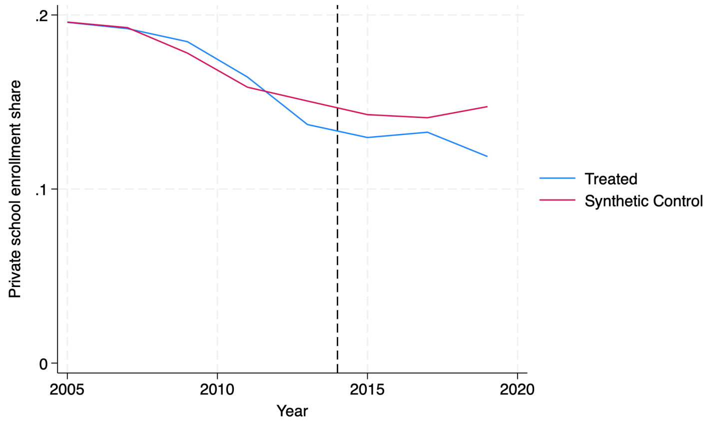
point the distance remains more constant. This is consistent with the idea that greater levels of unification in enrollment processes increase the charter enrollment share in NPS.

Based on the reported estimates in Table 3.2 as well as the plotted trajectories in Figure 3.13, UE did not affect NPS private school enrollment. The graph seems to show a downturn in the last two year period recorded in the data, suggesting some possibility of a negative effect with a longer time horizon than is measurable in the dataset. However, due to the limitations of the data and the somewhat visually imperfect pre-treatment fit, it is highly uncertain whether this is the case.

3.9 Washington, D.C.

While most UE programs emerged directly from previously decentralized processes, the Washington D.C. public school district (DCPS) UE system grew out of an existing CA

Figure 3.13: Synthetic control weights and plot for Newark private school enrollment



District	Weight
Anaheim	0
Baltimore	.234
Detroit	0
Jersey City	.385
Philadelphia	0
Pittsburgh	.138
Raleigh	0
San Diego	.243

Note: This figure plots private school enrollment share. The blue line represents the Newark school district, and the red line represents the synthetic control districts. The table on the right reports the weights assigned to each district in the donor pool, which includes partially centralized and non-centralized districts.

mechanism, implemented by the D.C. Board of Education in 2003. Prior to this policy change, parents' only option for attending an out-of-boundary school was to apply directly to the school principal, who ran admissions as they saw fit. As in Newark, some schools doled out seats to the first parents to camp outside the school before opening, and others used criteria that came across as arbitrary to many dissatisfied families [24].

The centralized system that ran from 2003 to 2014 allowed students to rank up to six DCPS schools, after which they would be placed following sibling and neighborhood priority. At this point, each charter school still had its own separate application and timeline [24]. This was particularly frustrating for D.C. families, as almost half of all public school students enrolled in charter schools prior to unification. In 2013, D.C. public charter schools voluntarily decided to align their timelines, holding lotteries on the same date. The next year, My School DC was rolled out as a UE system, and more than 40 charter schools joined. By 2017, over 90% of charters in DCPS participated in My School DC [13].

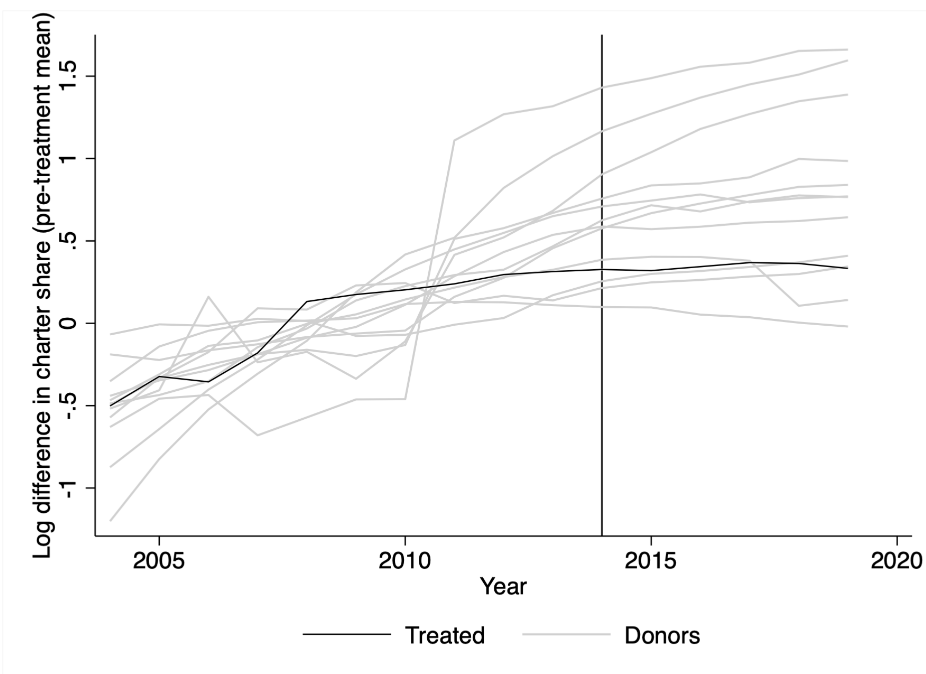
Like NOLA-PS, the high pre-treatment charter enrollment share in DCPS made it impossible to achieve sufficient pre-treatment fit of the outcome variable. The comparison of pre-treatment means is reported in Table 3.4. Thus the same adjustment to the outcome

Table 3.4: Pre-treatment averages of D.C. and control units

District	**Average charter share**
Baltimore	0.0190
Boston	0.0951
Cambridge	0.1997
Charlotte	0.0359
Columbus	0.2656
Minneapolis	0.1607
New York	0.0283
Oakland	0.0820
San Diego	0.0733
San Francisco	0.0352
Washington	**0.3085**
Winston Salem	0.0361

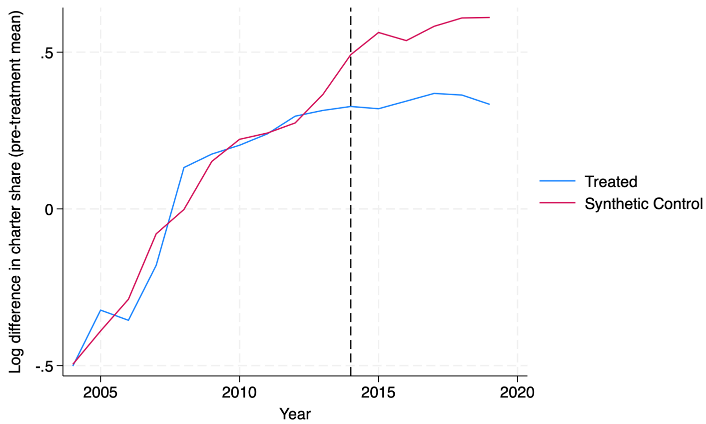
Note: This table displays the average charter share in the NOLA district and control districts prior to UE adoption in NOLA-PS in 2012. Charter enrollment share as a fraction of total public school enrollment is averaged across the years from 2006 to 2012.

Figure 3.14: Outcome paths for D.C. and control units



Note: This figure shows the trajectories of the D.C. school district and donor pool districts using the adjusted outcome variable. The log of pre-treatment average charter enrollment share for each district is subtracted from the log charter enrollment share in each period.

Figure 3.15: Synthetic control weights and plot for D.C. charter school enrollment



District	Weight
Baltimore	0
Boston	0
Cambridge	.078
Charlotte	.686
Columbus	0
Minneapolis	.235
New York	0
Oakland	0
San Diego	0
San Francisco	0
Winston Salem	0

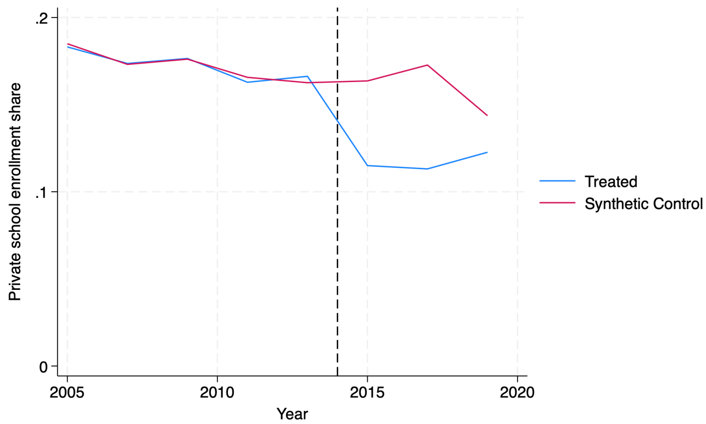
Note: This figure plots charter school enrollment share as a fraction of total public school enrollment. The blue line represents the D.C. school district, and the red line represents the synthetic control districts. The table on the right reports the weights assigned to each district in the donor pool, which includes partially centralized and non-centralized districts.

variable is used, taking the difference in log charter enrollment shares relative to the mean log charter enrollment share from the pre-treatment period. Adjusted trajectories for D.C. and control units are plotted in Figure 3.14. This is noted in Table 3.2 as well. No adjustment was needed for D.C. private school enrollment analysis.

The graph in Figure 3.15 seems to suggest that UE reduces the growth of charter enrollment share relative to pre-treatment means. The p-values in Table 3.2 indicate that this effect is not statistically significant. This could be due in part to the imperfect fit of the synthetic control to DCPS pre-treatment trends. However, as in the case of NOLA-PS, the perceived negative effect here could be overstated due to the adjustment of the outcome variable. Since the adjustment was made necessary due to the already large charter sector in DCPS, one can imagine that charter growth may be larger under the same conditions for districts with a smaller charter sector as there is more room to grow. On the other hand, the effect could also be understated if we believe that the DCPS charter sector is more inclined to expand because D.C. families are evidently more fond of charter schools.

On the other hand, UE adoption decreased private school enrollment share by 5 to 6

Figure 3.16: Synthetic control weights and plot for D.C. private school enrollment



District	Weight
Baltimore	.064
Boston	.061
Cambridge	.238
Charlotte	.009
Columbus	.237
Minneapolis	.008
New York	.004
Oakland	.013
San Diego	.329
San Francisco	.028
Winston Salem	.008

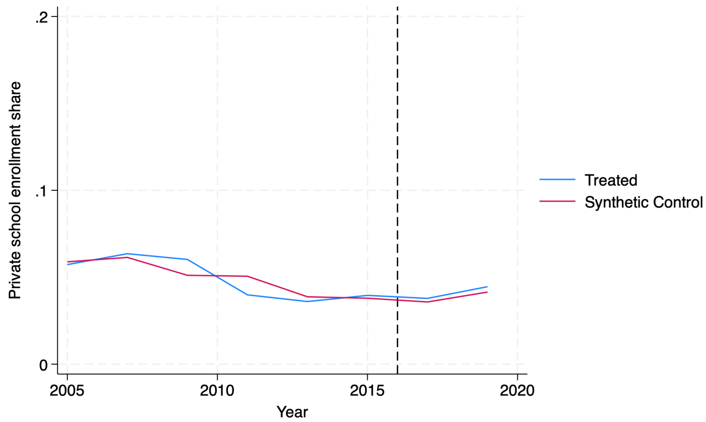
Note: This figure plots private school enrollment share. The blue line represents the D.C. school district, and the red line represents the synthetic control districts. The table on the right reports the weights assigned to each district in the donor pool, which includes partially centralized and non-centralized districts.

percentage points during the first three years following treatment. This effect is statistically significant based off of both the p-values and the standardized p-values in Table 3.2. The observed closeness of fit between the pre-treatment trends of the treated and synthetic control units in Figure 3.16 further validates this result. This effect does shrink at year 5 following treatment, which could indicate that short-term effects of UE adoption are stronger than long-term effects in this case.

3.10 Camden

In 2013, the Camden City School District (CCSD) was taken over by the state of New Jersey. This decision was announced by the governor after the New Jersey Department of Education classified 20 of its 23 schools to be "failing" based on metrics such as low graduation rates and state standardized test scores [25]. The leadership change spurred major changes across the district under the "Camden Commitment" initiative, a wide-reaching plan to improve the quality of CCSD schools following feedback from Camden families. One of its goals was to simplify enrollment processes and expand school choice for families, and in 2016 the Camden

Figure 3.17: Synthetic control weights and plot for Camden private school enrollment



District	Weight
Anaheim	0
Baltimore	0
Detroit	.767
Jersey City	.233
Philadelphia	0
Pittsburgh	0
Raleigh	0
San Diego	0

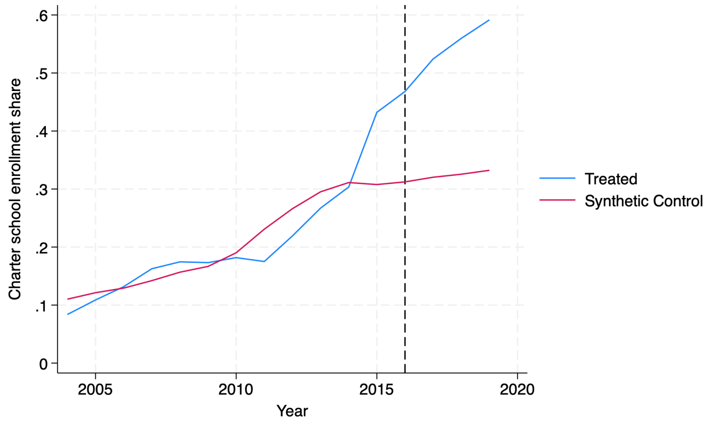
Note: This figure plots private school enrollment share. The blue line represents the Camden school district, and the red line represents the synthetic control districts. The table on the right reports the weights assigned to each district in the donor pool, which includes partially centralized and non-centralized districts.

Enrollment system was put into place, replacing 17 different charter school applications and introducing a streamlined way to apply to all public schools citywide [26].

Under the new UE system, students could still choose to attend their zoned neighborhood school, and only those who wanted to attend a different school the following year would need to submit an application. The application allowed each student to rank up to 10 schools, and families could link siblings' applications to ensure that they would all be assigned to the same school. Students would be given a single offer, and special magnet school criteria (report cards and interviews) were considered in the same matching process as all other public schools to ensure efficiency and fairness [26]. As part of the rollout of Camden Enrollment, a public campaign called "Choose Camden" was launched to raise awareness and provide support to families navigating the new system. Still, 29% of respondents who did not submit an application during the first year of implementation were reportedly unaware of the option [13].

Based on the estimates reported in Table 3.2 as well as by visual inspection of the outcome trends graphed in Figure 3.17, the implementation of UE in Camden did not affect the share of students enrolling in private school.

Figure 3.18: Synthetic control weights and plot for Camden charter school enrollment



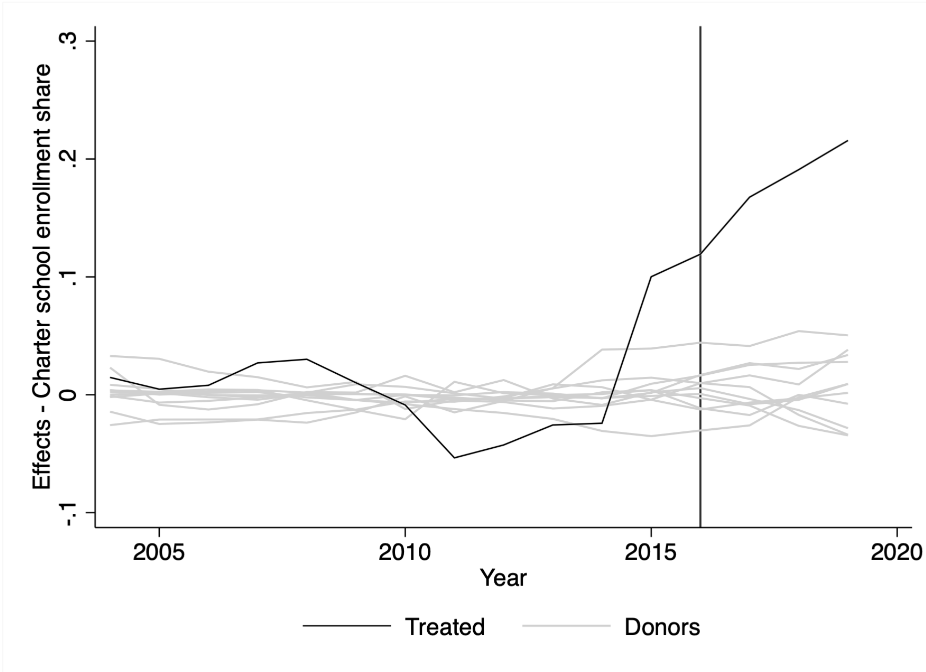
District	Weight
Anaheim	0
Baltimore	0
Detroit	0
Jersey City	0
Philadelphia	.894
Pittsburgh	0
Raleigh	0
San Diego	.106

Note: This figure plots charter school enrollment share as a fraction of total public school enrollment. The blue line represents the Camden school district, and the red line represents the synthetic control districts. The table on the right reports the weights assigned to each district in the donor pool, which includes partially centralized and non-centralized districts.

However, UE implementation significantly boosted charter enrollment share, by as much as 25 percentage points three years after its adoption. The p-values from the placebo test indicate that this result is significant in every post-treatment period, but the p-values standardized for pre-treatment fit do not. In Figure 3.18, the post-treatment CCSD charter enrollment diverges visibly from the synthetic control. Furthermore, Figure 3.19 displays the pre- and post-treatment fit of each district to the constructed synthetic control. Camden has the worst post-treatment fit by far, but also matches the pre-treatment trends less closely than the control units.

Based on the context of the CCSD takeover and subsequent reforms, there is some uncertainty regarding whether the estimated charter enrollment effects here are overstated or understated. As a part of the effort to improve school quality, nine district schools deemed under-performing were converted to “renaissance schools” in 2014 and 2015, governed by district-charter collaborations [27]. While some sources consider these renaissance schools to be charter schools, the NCES dataset codes them as traditional public schools, and thus my analysis classified them as district schools. If they had been categorized as charters in 2014 or 2015, the estimated effects would be more exaggerated. Another action taken by

Figure 3.19: Effects plot for Camden and control units



Note: This figure plots the post-treatment effects of UE adoption on charter school enrollment share for the Camden school district. The gray lines display the placebo effects computed for the donor pool districts.

the state government was to close eight district schools between 2013 and 2021 [28]. While it is possible that UE allowed families to more easily apply to attractive charter schools, it is also possible that these changes merely artificially boosted charter enrollment share by giving families less district school options to choose from.

4 Conclusion

Unified enrollment initiatives have been lauded in Denver for successfully streamlining the school choice process and improving access to better educational opportunities. At the same time, they have also failed to gain traction in Boston and Detroit, districts in which proponents have been working to launch a UE program for years. Recently, the hope for UE is that giving families easy access to public education options will be able to combat the ongoing decline in public school enrollment. Synthetic control and event study analysis in this paper show that overall, UE adoption does boost public school enrollment, and in particular boosts charter enrollment.

While not all districts saw significant effects of UE adoption on charter and private school enrollment share, it is encouraging to see that the district-level estimated effects effects point in the same direction as overall estimated effects. For charter schools, both Camden and Newark saw significant positive effects, suggesting that a more streamlined enrollment process does make families more likely to enroll their children in charter schools. For private schools, all statistically significant effects measured, in D.C. and Denver, were negative. This indicates that policy reducing barriers to choice within the public school system can keep children in public schools.

Interestingly, in no districts did UE boost charter enrollment and reduce private school enrollment simultaneously. This suggests that families are not just substituting charter enrollment for private school enrollment, but are actually also enrolling more in traditional district schools as a result of UE policies. We observe this even in DCPS, where traditional district schools were already in a central match prior to treatment, though the charter effects in this case are more uncertain due to the adjustment of the outcome variable. On the other hand, these results also suggest that in the cases where UE causes charter school enrollment to increase, the change is driven by families switching over from traditional district schools, not from private schools.

Both the event study and the varying result sizes indicate another crucial takeaway. Newark's UE adoption caused families to choose charter schools over district schools, while Denver's UE adoption caused families to enroll less in private schools without affecting the charter-district balance in public schools. Depending on a district's goals, it may be desirable to increase public school enrollment as a whole, but not to shift district enrollment to charters. Thus it is necessary to more closely examine the context of the district and compare it to that of the districts studied here.

The effects measured here have important policy implications. It is notable that in none of the districts studied did streamlining choice policy drive more families to private schools. Given that the departure of more economically privileged families from the public school system is detrimental to public school funding and educational equity, this result provides a convincing argument for considering UE systems in other districts. It is also likely that enabling more students to enroll in charter schools may be beneficial to students, if it is true that charters especially drive achievement for low-achieving students [3] and that students selecting into charter schools through UE has a positive impact on student achievement overall [8]. In the future, it would be interesting to analyze separately the effect of adopting CA systems on enrollment–perhaps students would more often enroll in district schools because it is easier than enrolling in a charter school. Another question that remains is which groups of students are affected by the implementation of school choice assignment mechanisms. If the students who switched into a charter after UE adoption were the lower achieving students who would benefit from attending a charter school, the argument for UE would be more convincing than if only families with more resources were putting time into navigating the UE application system.

A limitation of this study is that private school enrollment data is not collected yearly. With more pre-treatment and post-treatment data, it may be possible to produce more accurate estimates based on more granular trends. Another avenue for future work involves expanding the number of districts studied and the time horizon. Some adopters of UE, such as Indianapolis and Chicago, are too recent to include in this analysis as there are not enough post-treatment periods to adequately measure the treatment effect. Adding more control districts to the donor pool may also improve the pre-treatment fit and synthetic counterfactual accuracy.

A District Identification

Information on when each district used in my analysis implemented their full CA, partial CA, or UE programs were compiled from a variety of sources. These sources are reported in Table A.1, which provides a summary of the policies of each district and the year each of these systems was put in place. In some cases, such as with Columbus and Minneapolis, I did not find the exact year that the assignment program began, but I have recorded the earliest year that I could find evidence of its existence.

A.1 Policy Start Dates

For charter enrollment effects, I use 2004 as the first year of my analysis. For private enrollment effects, I use 2005 as the first year of my analysis. Note that Baltimore only adopted partial CA in 2005. I chose to still use 2004 as the first year for charter school effects because I noticed that when I ran the SCM weight optimization, Baltimore was assigned zero weight in all charter enrollment analyses. Pushing the start year back to 2004, which was the next latest out of the start years, improved the pre-treatment fit and increased the precision of my results.

A.2 Partial Centralization

There are two school districts that I designated to be partial CA. These district policies did not cleanly fit into centralized student assignment mechanisms or decentralized school choice. Baltimore City Public Schools prior to 2005 operated solely on a neighborhood assignment system prior to 2005, with four citywide selective admission schools which required individual applications to be considered. In 2005, Baltimore allowed all 8th grade students to enter a choice lottery to choose the high school they would attend in the fall. In 2010, 5th graders were given the ability to submit the same application to choose their middle school [30].

Table A.1: District policy summary table

District	**Policy Type**	**Start Year**	**Source**
Anaheim	No CA	N/A	[29]
Baltimore	Partial CA	2005	[30]
Boston	CA	1975	[2]
Cambridge	CA	1981	[31]
Camden	UE	2016	[26]
Charlotte	CA	2001	[32]
Columbus	CA	pre-2003	[33]
Denver	UE	2011	[13]
Detroit	No CA	N/A	[12]
Jersey City	No CA	N/A	[34]
Minneapolis	CA	pre-1993	[35]
New Orleans	UE	2012	[21]
New York	CA	2003	[36]
Newark	UE	2014	[23]
Oakland	CA	2004	[37]
Philadelphia	No CA	N/A	[38]
Pittsburgh	No CA	N/A	[12]
Raleigh	No CA	N/A	[39]
San Diego	Partial CA	pre-2001	[40]
San Francisco	CA	1983	[41]
Washington D.C.	CA	2003	[24]
Washington D.C.	UE	2014	[13]
Winston Salem	CA	2000	[32]

Though the amount of choice in Baltimore evolved over this time, centralized school choice is still not offered to all students at all years.

In San Diego, the options for school choice are VEEP, magnet, charter, and open-enrollment programs. VEEP, or the Voluntary Enrollment Exchange Program, is an attempt to racially integrate schools in SDUSD. Small groups of schools are grouped into allied patterns, and students can apply to attend and be bused to another school in their allied pattern. Magnet and charter schools in SDUSD, like in most other districts, have their own application processes. Other schools in the district are designated as open-enrollment, and students are free to apply a school outside of their neighborhood. The VEEP, magnet, and open-enrollment schools each have centrally administered lotteries. I have also classified this as partial CA, as students must fill out separate applications for the VEEP and open-enrollment programs, for instance.

A.3 NCES Identification

For most school districts, I was able to identify schools using NCES or state-assigned school IDs. I then identified corresponding charter and private schools by city. Here, I note a few exceptions.

For New York City, the district schools were easily identifiable by state IDs beginning with 3. The charter and private school identification was more difficult, as I needed to include those labeled "New York" as well as those located in "Flushing", "Bronx", etc. To do this, I identified all cities reported by schools within the NYC school district and included charter and private schools in each of those cities. I followed the same process for Boston, as some schools reported their location city to be Allston, Jamaica Plain, etc.

The NCES dataset mislabeled many charter schools in Denver as traditional public schools. For the entire dataset, I looked for keywords like "CHRTR" or "KIPP" and relabeled them as charter schools. In the case of Denver Public Schools, I additionally found a list of district and charter schools in the district and corrected the labels manually.

For the North Carolina school districts, it was more straightforward to identify charter schools by state ID. For instance, Charlotte-Mecklenberg Schools had three-digit state IDs beginning with "60" while associated charters had state IDs beginning with "60" and ending with a letter. Winston-Salem and Raleigh were identified similarly.

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