Navigating Competitive Pressures: School Responses to Competition and the Distributional Effects on Student Achievement

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Abstract

This paper examines the equity-efficiency implications of traditional public schools' (TPSs) responses to increased competition from charter schools. Using administrative data from North Carolina, I find that TPSs respond to student and teacher attrition to charter schools by reducing the number of classes, resulting in increased class sizes and higher student-teacher ratios. To maintain school proficiency rates, TPSs strategically reassign high-quality teachers to low-achieving and economically disadvantaged students. These effects remain consistent even after accounting for changes in school composition. Furthermore, I develop and estimate an empirical model of school choice and competition to analyze the impact of charter sector expansion. The findings indicate that expanding charter schools promotes a more equitable distribution of high-quality teachers within TPSs. Additionally, optimizing teacher-student matching emerges as an effective strategy to improve allocative efficiency.

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1 Introduction

School choice initiatives are increasingly common in education systems across the world. The efficacy and distributional impacts of such initiatives are highly contested and have implications for hundreds of millions of children. Proponents of school choice argue that, in addition to providing more educational options, it introduces competitive forces to the public school system and incentivizes traditional public schools (TPSs) to raise their quality, creating "a tide that lifts all boats" (Hoxby, 2003). However, existing empirical studies yield mixed results regarding the impact of charter school entry on the quality of nearby TPSs (Gill and Booker, 2008; Ridley and Terrier, 2018; Slungaard Mumma, 2022). The reasons for these inconsistent findings are not yet clear.

There are at least two possible explanations for these disparities. First, the competitive effect of school choice significantly depends on how schools respond to competitive pressure. Some schools may adopt innovative teaching methods and improve resource allocation to retain students and enhance performance, while others may struggle to respond effectively due to financial constraints and resource limitations. Second, competition strategies may inadvertently favor certain groups of students over others. For instance, schools might allocate more resources to students who can boost the school's performance statistics, potentially neglecting students who require additional support. Understanding how schools navigate competitive dynamics and the resultant impacts on different students provides essential insights into the mechanisms through which competition shapes school quality. These insights are crucial for policymakers to design equitable and effective school choice policies. However, our current body of empirical evidence on this topic remains limited.

This paper aims to fill this gap by examining the equity-efficiency implications of schools' responses to increased competition, particularly focusing on the allocation of teaching resources. It also develops and estimates an empirical model of school choice and competition to explore the equilibrium effects of alternative policy designs that might

achieve greater equity and efficiency gains. To do this, I leverage the charter school expansion reform in North Carolina, which created unique variations in exposure to competition from charter school openings across TPSs and over time. Since the charter school movement began in 1996, North Carolina has experienced a significant increase in the number of charter schools and their enrollments, especially after the 2011 education reform bill that lifted the cap on charter schools. I employ a stacked difference-in-difference (DID) model to identify the causal impacts of charter school openings, comparing TPSs located near new charter schools to those situated farther away.

I begin by examining the impacts of charter school openings on how TPSs restructure classes, focusing on the number of classes, average class size, and student-teacher ratio. Results show that subsequent to substantial reduction in both student enrollment and the number of teachers within TPSs, TPSs restructured classes through reducing the number of classes by approximately 7.00%. Concurrently, there is a significant rise in class sizes and student-teacher ratios: average class sizes in TPSs increase by 1.63% in Math and 1.71% in English Language Arts (ELA); the student-teacher ratio increases by 5.23% in Math and 4.18% in ELA.

Next, I analyze how TPSs adjust teacher allocation across grades and student groups in response to competitive pressures, assessing the implications for equity and efficiency by investigating which teachers are matched to which students. This involves a detailed exploration of how TPSs redistribute high-quality teachers—characterized by value-added metrics, teaching experience, and educational level—across diverse student groups, differentiated by economic status and academic ability. Additionally, I examine whether TPSs enhance teacher-student matching in terms of gender and racial congruence, and teachers' relative strengths in educating different students.

Results show that TPSs adopt compensation strategies by assigning more high-quality teachers to more disadvantaged students including students from economically disadvantaged backgrounds and students with lower academic achievement records. Teachers

with more than five years of experience, graduate degrees, and above-average value-added scores experience a more pronounced increase in the proportion of economically disadvantaged students they teach, along with a significant decline in the average baseline scores of their student population, compared to other less-qualified teachers within the same school. Importantly, these effects remain consistent after accounting for changes in the composition of both teachers and students at the school level before and after the introduction of charter schools. Nevertheless, charter school openings have no significant effect on teacher-student matching in TPSs. Nearby charter openings do not enhance teacher-student gender or racial matching, nor do they improve matching based on teachers' relative strengths in teaching high-achieving or economically disadvantaged students.

While the reduced-form results credibly demonstrate that schools respond to competition by reallocating teaching resources and prioritizing disadvantaged students, they do not quantify the extent to which this reallocation impacts student achievement or the equilibrium effects of alternative policy designs that are of significant policy interest. Thus, in the second part of this paper, I develop and estimate a structural model of school choice and competition to provide a deeper understanding of how competitive forces impact the distribution of student achievement. This model incorporates both students' school choice and schools' choice of teacher reallocation, extending beyond quasi-experimental evidence in two significant ways.

First, the model decomposes the effects of charter school openings on student achievement, separating the impacts of student sorting (peer effects) from those of teacher reallocation (competition channel). This decomposition elucidates the mechanisms through which competition affects educational outcomes. Second, the model quantifies the equilibrium effects of alternative school choice designs, providing valuable insights for policymakers. It identifies policy measures that effectively balance equity and efficiency in education, thereby facilitating the optimization of school choice policies to improve over-

all student outcomes.

The estimates of the school choice and competition model reveal heterogeneity in students' preferences for school quality and teacher quality. High-achieving students exhibit more pronounced preferences for school quality and the availability of high-quality teachers compared with low-achieving students. On the supply side, I find that TPSs value both school proficiency rates and market share. TPSs face a trade-off in determining the teacher-to-student allocation regime. Allocating a greater share of high-achieving students to high-quality teachers potentially bolsters market share, recognizing that such students value access to high-quality teachers. Conversely, distributing high-quality teachers more evenly, especially among low-achieving students, is shown to elevate school proficiency rates more effectively, as high-quality teachers have larger positive effects on these students' proficiency levels.

I then use the estimated model to conduct a counterfactual analysis of the charter school expansion policy. I find that North Carolina's 2011 policy of lifting caps on charter schools increases access to high-quality teachers for low-achieving students, leading to a 4.10 percentage point rise in the share of these students assigned to high-quality teachers. Consequently, there has been a notable improvement in both proficiency rates and test scores of low-achieving students. However, average test scores for high-achieving students have declined due to reduced access to high-quality teachers. Further decomposition of the policy effects indicates that TPSs' teacher reallocation strategy plays a major role in the impacts of charter expansion on student achievement.

To assess whether the allocative efficiency of charter school expansion policies can be improved, I conduct a counterfactual analysis that enables schools to enhance teacher-student matching based on teachers' comparative advantages. The findings indicate that optimizing teacher-student matching is an effective strategy for achieving efficiency gains, resulting in improved test scores for both high-achieving and low-achieving students.

This paper seeks to advance the understanding of competitive forces in education markets and on how to utilize school choice initiatives to benefit students across the board, particularly the least fortunate. Within this realm, it aims to make three main contributions. First, this study relates to the literature on the competitive effects of school choice policies. Some studies find charter entry improves TPSs' quality, especially when the entrant is high-performing or located in close proximity to TPSs (Cordes, 2018; Cremata and Raymond, 2014). In other contexts, however, the competitive incentives for TPSs to raise quality are muted (Slungaard Mumma, 2022), probably because TPSs and charters are not close substitutes (Gilraine et al., 2021) or charters drain resources from TPSs (Han and Keefe, 2020; Ladd and Singleton, 2020; Bifulco and Reback, 2014). To explain the non-uniform competitive effects of charter entry, a growing literature investigates how incumbent schools respond to competitive pressure. They find that increased competitive pressure affects teacher hiring (Jackson, 2012) and expenditures on instruction, support services, and capital construction (Cook, 2018; Ridley and Terrier, 2018).

This paper is among the first studies to examine how incumbent schools reallocate teaching resources in reaction to increased competition. To the best of my knowledge, this work provides the first causal evidence on whether incumbent schools reshape classes and adjust teacher-to-student assignment rules – and, in particular, decisions about which students are assigned the highest quality teachers – in response to competition from charter schools. Since both class size and high-quality teachers are critical determinants of student achievement (Angrist and Lavy, 1999; Krueger, 2003; Rockoff, 2004; Rivkin et al., 2005; Chetty et al., 2014a), how TPSs adjust these resources can be a primary mechanism for explaining the non-uniform competitive effects of charter entry on TPSs' quality, and their distributional consequences.

Second, this study builds on the literature examining the equilibrium effects of school choice, where researchers have developed structural models to study schools' entry decisions (Dinerstein and Smith, 2021), quality choices (Neilson, 2021; Mehta, 2017; Allende,

2019; Gilraine et al., 2023), classroom segregation choices (Crema, 2023), and teaching to whom choices (Bau, 2022) in response to competition, mostly between public and private schools. This paper develops and estimates the first school choice and competition model that explicitly incorporates schools' decisions on teaching resource allocation in response to competitive pressures. This model uniquely evaluates how these responses impact the equity and efficiency of teaching resource distribution and their heterogeneous effects on different student groups. From a policy perspective, this school competition model is immediately valuable to policymakers interested in expanding school choice. It reliably predicts the equilibrium effects of alternative policy measures and facilitates the optimization of policy designs.

This paper is closely related to the work of Gilraine et al. (2023), which models schools' quality choices under competition and evaluates the impacts of counterfactual school choice policies on aggregated market outcomes. My paper differs in several key aspects. First, this paper uniquely models schools' decisions on teaching resource allocation under competition, identifying it as a primary mechanism through which school choice policy influences the quality of incumbent schools. Second, it exclusively focuses on the welfare of students who remain in TPSs following the introduction of charter schools, who represent the majority in the market. Third, this study investigates the heterogeneous impacts of charter school expansion on both advantaged and disadvantaged students, highlighting a more pronounced positive effect on the latter group. Furthermore, it explores how teacher-student matching processes can enhance allocative efficiency under the charter expansion policy.

This study also builds on the literature examining teacher-student matching, which shows significant impacts on student academic achievement, behavior, and engagement (Dee, 2005, 2007; Muralidharan and Sheth, 2016; Eble and Hu, 2020). Motivated by this evidence, recent research has focused on estimating teachers' comparative advantages in teaching different students (Delgado, 2021; Bates et al., 2022; Biasi et al., 2021; Graham

et al., 2022). This paper contributes to the literature by providing new evidence on how education policies influence teacher-student matching in public schools and the role of matching in enhancing the efficiency of school choice policies.

The subsequent sections of this paper are structured as follows. In Section 2, I provide an overview of the background information of charter schools in North Carolina and the dataset employed in this study. Section 3 outlines the empirical methodology utilized to examine the causal impact of charter school openings and the results derived from the reduced-form analysis. Moving forward, Section 4 introduces the school choice and competition model while Section 5 provides the model estimation methods and results. In Section 6, I present the findings from the counterfactual analysis, and finally, Section 7 offers the conclusions.

2 Institutional Background and Data

2.1 Charter Schools in North Carolina

Charter schools are publicly funded schools that operate independently of traditional public school districts. They are part of the state's public education system but have more autonomy in terms of curriculum, operations, and management compared to traditional public schools. In North Carolina, charter schools are authorized and overseen by the North Carolina Department of Public Instruction (NCDPI) and the North Carolina State Board of Education. Similar to traditional public schools, charter schools in North Carolina are also held accountable for academic performance and financial management.

North Carolina has seen a significant increase in the number of charter schools and charter school enrollment since its charter school movement 1996 (see Figure 1). North Carolina had a cap on the number of charter schools that could operate in the state, which was originally set at 100 schools. In 2011, North Carolina passed a landmark education reform bill that effectively lifted the cap on the number of charter schools. As of the 2022-

2023 school year, there are 206 charter schools in North Carolina and more than 10% of public school students study in charter schools.

Table 1 compares the school and student characteristics between charter schools and traditional public schools in North Carolina. Charter schools are more likely to locate in urban areas while TPSs have larger school enrollment. Charter school students are more likely to be White, and less likely to be economically disadvantaged. Charter school students have higher proficiency rates in ELA and Math. Moreover, the average test scores in Math and ELA are higher in charter schools than in TPSs.

2.2 Data

This study combines multiple sources of data. The main source I utilize for the analysis is the administrative data from the North Carolina Education Research Data Center (NCERDC) and the North Carolina Department of Instruction (NCDPI). These datasets provide longitudinal records on students, teachers, and schools/districts. It covers students from grade 3 to grade 8 in all public schools in North Carolina. Student-level data includes student school enrollment information, demographics, course membership, geocoded home address, and student performance in mathematics and ELA. Test scores in Math and ELA are both standardized to have mean 0 and standard deviation 1 for each grade-year among public school students.

Teacher-level data includes teacher education level, teaching experience, teaching certification, and salary. An important feature of NCERDC data is that, students can be linked to teachers in each course through the course membership information, facilitating the analysis of teacher-to-student assignment. I restrict the analytical sample to 2006-07 through 2016-17 school years for which course membership data and student home address data are available. This paper mainly focuses on students from grade 4 to grade 8 in TPSs. I exclude students in grade 3 because I cannot observe their prior test scores so I cannot estimate teacher value-added for their teachers. In my analysis sample, I have

more than 600,000 students and more than 2,300 schools in each academic year.

NCERDC and NCDPI also provide rich information on school and school districts characteristics, including school locations, served grades, school enrollment, student body composition, and school quality. I supplement these school-level datasets with the Public Elementary/Secondary School Universe Survey data from Common Core of Data to provide more robust school characteristics information.

In the estimation of the school choice and competition model, I employ extra data to generate instrumental variables. First, I use demographic information at census tract level from the American Community Survey (ACS) data to construct instrument variables for school peer composition, including racial composition and median household income. Second, I use the teacher salary schedule data in North Carolina from 2006 to 2017 to construct instruments for school quality and teacher quality. Last, I use the higher education institutes enrollment and characteristics data between 2010 and 2017 from the National Center for Education Statistics' Integrated Postsecondary Education Data System (IPEDS) to construct instruments for teacher quality.

2.3 Measurement of Teacher Value-Added

In this paper, I utilize three measures to assess teacher quality: educational attainment, teaching experience, and value-added metrics. I follow the method proposed in Chetty et al. (2014a) to estimate each teacher's value-added. Basically, the estimation method in Chetty et al. (2014a) predicts teachers' value-added based on the average test scores of each teacher's students, while controlling for a rich set of student-level characteristics including lagged test scores and demographics, and teacher-level, classroom-level, and school-level characteristics. After controlling for a rich set student-, class-, and school-level characteristics, the estimated teacher value-added is unbiased predictor of teacher quality. Appendix A provides additional details about teacher value-added estimation.

Teachers' comparative teaching advantages: In analyzing teacher-student matching,

I identify teachers' comparative advantages by estimating their value-added for different groups of students using the methodology described above. I then compare the value-added scores for teaching various student groups to identify their comparative advantages[1]. For instance, if a teacher's value-added in teaching high-achieving students is higher than their value-added in teaching low-achieving students, the teacher is identified as having a comparative advantage in teaching high-achieving students[2] [3]. I estimate teachers' value-added not only in teaching high- and low-achieving students but also in teaching economically advantaged and disadvantaged students.

Next, I link the information on individual teachers' comparative advantages to student-level data and for each teacher, I calculate the fraction of their students who are well-matched with the teacher. For instance, students matched well with teachers include high-achieving (low-achieving) students taught by teachers with comparative advantages in teaching high-achieving (low-achieving) students.

Classifying teachers into two comparative advantage groups based on group-specific value-added scores can be inaccurate, as a higher value-added score for one student group might simply reflect noise in the value-added estimations rather than an actual comparative advantage. To address this issue, I construct an alternative measure of matching quality, $Value_{ljt}$, using continuous group-specific value-added. This measure captures how valuable a match is by calculating a teacher's total contribution to student achievement in a school.

$$Value_{ljt} = VA_{lt}^{k=1} * Fraction_{ljt}^{k=1} + VA_{lt}^{k=0} * (1 - Fraction_{ljt}^{k=1})$$

[1] I standardize the estimated group-specific teacher value-added at the corresponding student group level to make the group-specific teacher value-added comparable across student groups.

[2] If the absolute difference in value-added scores between the two groups is smaller than the 10th percentile of the distribution of absolute differences across all teachers, the teacher is classified as having no comparative advantage.

[3] Minority students, such as economically disadvantaged students, may not appear in each teacher's class due to the relatively smaller size of the minority groups. To improve the accuracy in the estimation of group-specific teacher value-added, I exclude teachers with fewer than 5 economically disadvantaged students in the estimation of teacher value-added for economically disadvantaged students.

where $VA_{lt}^{k=1}$ is teacher l's value-added for student group k. $Fraction_{ljt}^{k=1}$ is the fraction of students from group k among teacher l's overall student population in school j and in year t. In other words, teacher l's total contribution to student achievement in school j and in year t is a weighted average of teacher l's group-specific value-added, with the weights determined by the size of each student group assigned to the teacher. Intuitively, this function suggests that teachers with higher value-added in teaching high-achieving students, when assigned a larger proportion of high-achieving students, contribute more significantly to overall student achievement.

3 Empirical Analysis of School Competitive Reactions

In the first part of the study, I examine the causal effects of charter openings on several equilibrium outcomes in TPSs. Specifically, after a charter school enters the market, I address the following questions: (1) How do charter openings affect enrollment, teacher and student composition, and academic performance in TPSs? (2) Do TPSs adjust their class structures in response to charter school competition? (3) Do TPSs reallocate teachers across grades and student groups when faced with competition?

3.1 Identification

I employ a stacked difference-in-difference model to identify the causal impacts of charter school openings, leveraging the temporal and spatial variation in TPSs' exposure to new charter schools. Treatment schools are defined as TPSs located within a 5-mile radius of a new charter school, with both institutions serving at least one overlapping grade. These treatment schools are compared to control schools located beyond the 5-mile radius [4].

The choice of a 5-mile radius is based on the fact that approximately 75% of elementary and middle school students in the sample of North Carolina live within 5.38 miles of their

[4]To ensure the treated schools and untreated schools are comparable, I restrict the analysis sample to schools located within 40 miles of new charter schools

schools. Thus, a new charter school located within a 5-mile radius is expected to exert the strongest competitive pressure on TPSs. Additionally, this 5-mile radius aligns closely with the mean distance radius used in the existing literature [5]. I explore the sensitivity of the main results to the choice of distance radius in Appendix B.

In my sample, TPSs experienced charter school entries at different times, with some TPSs being exposed to multiple nearby charter openings across various years. Numerous studies have shown that treatment effect estimates from DID models can be biased when the treatment effect is heterogeneous in a staggered treatment adoption design (De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Callaway et al., 2021; Sun and Abraham, 2021). To address this issue, I follow the strategy in Cengiz et al. (2019) and Deshpande and Li (2019) by generating school cohort datasets, denoted as $cohort_c$. Each cohort dataset includes two groups of schools. The first group is the treatment group, consisting of schools exposed to a new charter entry nearby in year c, but not experience any additional charter entries in the six-year period extending from year $c-3$ to year $c+2$. The second group is the control group, which includes schools that do not experience any nearby charter entry in the six-year period extending from year $c-3$ to year $c+2$. I stack all the cohort datasets to create my analytic sample.

The reduced-form analysis comprises two parts. The first part uses school-level data to examine the impact of charter openings on school-level outcomes in TPSs, including school enrollment, teacher and student body composition, school proficiency rates, average test scores, and class structure. The estimation equation is specified as follows:

$$Y_{jt} = \beta Post_t * Treat_j + X_{jt} + \tau_{cj} + \tau_{ct} + \epsilon_{jt} \tag{1}$$

where Y_{jt} are the outcomes of school j in year t. $Post_t$ is an indicator for observations after the charter openings. $Treat_j$ is an indicator that is equal to 1 if school j is located

[5] In the literature on the competitive effects of charter schools on TPSs, there is no consensus regarding what constitutes a nearby charter school, and researchers employ different distance radii to define treatment schools and control schools. The distance radius used in studies ranges from 2 miles (Slungaard Mumma, 2022), 2.5 miles (Gilraine et al., 2021), 5 miles (Gilraine et al., 2021), 10 miles (Jackson, 2012), and 20 miles (Jackson, 2012; Gilraine et al., 2023).

within 5 miles of the new charter school and serves overlapped grades with the new charter school. X_{jt} are school characteristics including lagged average scores in Math and ELA. τ_{cj} are the school-by-cohort fixed effects and τ_{ct} are cohort-by-year fixed effects. The parameter β is the main coefficient of interest and it recovers the effect of being exposed to a new charter school nearby on school-level outcomes.

The second part uses the teacher-level data to examine how charter openings affect the allocation of teachers to students in TPSs. The estimation equation is specified as follows:

$$\begin{aligned} Y_{ljt} =& \beta Post_t * Treat_j + \beta_h Post_t * Treat_j * Teacher_{lt}^{high} + Teacher_{lt}^{high} * Post_t + Teacher_{lt}^{high} * Treat_j \\ &+ \sum_z Teacher_{lt}^{z} + X_{jt} + \tau_{cj} + \tau_{ct} + \epsilon_{ljt} \end{aligned} \tag{2}$$

Y_{ljt} represent the outcomes of teacher l in school j in year t. $Teacher_{lt}^{high}$ is a holistic indicator of high-quality teachers, defined by the combination of above-average value-added scores, possession of a graduate degree, and more than five years of teaching experience. $Teacher_{lt}^{z}$ consists of three teacher quality variables indicated by z: education level (measured by whether teacher l has a graduate degree), years of teaching experience, and teacher value-added. I interact the holistic indicator of high-quality teachers—encompassing value-added, teaching experience, and educational attainment—with $Post_t * Treat_j$ to explore the heterogeneous effects between high-quality teachers and their less-qualified counterparts, while controlling for the individual teacher quality variables. All other variables are defined as previously described.

The parameters β and β_h are the main coefficients of interest. β captures the impact of exposure to a new nearby charter school on less-qualified teachers—those who lack graduate degrees, have five or fewer years of experience, or exhibit below-average value-added scores. The coefficient β_h on the interaction term with $Teacher_{lt}^{high}$ represent the differential effects of exposure to a nearby new charter school specifically on high-quality teachers.

In the examination of teacher-to-student allocation, I generate outcome variables that

portray the characteristics of students assigned to individual teachers. To be precise, I calculate the proportion of economically disadvantaged students among the entire cohort of students instructed by each teacher, along with the average prior-year test scores (baseline scores) in either Math or ELA. For the analysis of teacher-student matching, I define a teacher-level matching variable as the proportion of a teacher's students who exhibit a good match with the teacher across three distinct dimensions: 1) gender and racial alignment between teachers and students; 2) students' economically disadvantaged status and the teacher's comparative advantage in teaching economically disadvantaged students; 3) students' baseline achievement level and the teacher's comparative advantage in teaching high-achieving students.

Evaluation of Parallel Trend Assumption: A key challenge in identifying the causal effects of charter school openings is the non-random selection of their locations. The validity of using a DID model to estimate causal impacts depends on the assumption that TPSs located near new charters and those located farther away exhibit parallel trends in outcomes prior to the introduction of charter schools. I examine the parallel trend assumption using the event study model specified below and demonstrate that there is no difference in the trends of outcomes preceding the charter openings.

$$Y_{(l)jt} = \sum_{e \in [-3,2]} \theta_e * D_{j,t+e} + X_{(l)jt} + \tau_{cj} + \tau_{ct} + \epsilon_{(l)jt} \tag{3}$$

where $Y_{(l)jt}$ are the outcomes at school- or teacher-level. $D_{j,t+e}$ is a series of lead and lag indicator variables for when the charter school opened within 5 miles of school j and serves overlapped grade with school j. 3 lags and 3 leads are included respectively, which are indicated by $t + e$. The first lag, $D_{j,t-1}$, is omitted to capture the baseline difference between treated and control schools. $X_{(l)jt}$ is a vector of school- or teacher-level characteristics. All other variables are defined as before. Appendix D provides the main results and there is no evidence of a violation of the pre-trend in all the analyses.

Triple Difference-in-Difference: To ensure that the main results are not confounded by unobserved time-variant factors, I employ a triple DID model to control for unob-

served heterogeneity that may vary across schools and over time. This approach incorporates an additional control group: non-overlapped grades (grades not served by both the TPS and the new charter) in TPSs. Although these non-overlapped grades are not directly affected by the charter school intervention, they are subject to the same time-varying confounders as the overlapped grades within the same school. Consequently, in the absence of the intervention, the trends in outcomes would have been parallel across the overlapped and non-overlapped grades within the same school.

Specifically, I generate three layers of differences: 1) the difference in outcomes among overlapped grades between TPSs located within 5 miles of the new charter and those beyond this proximity; 2) the difference in outcomes among non-overlapped grades between proximal and non-proximal TPSs to the new charter schools; 3) the third difference is to compare the double difference generated by 1) and 2) before and after the charter entry. The specification of a triple DID model is presented below:

$$
\begin{aligned}
Y_{ljt} = {} & \beta_1 Post_t * Treat_j + \beta_2 Post_t * OverlapGrade_{gj} + \beta_3 Treat_j * OverlapGrade_{gj} \\
& + \beta_4 Post_t * Treat_j * OverlapGrade_{gj} + \beta_h Post_t * Treat_j * OverlapGrade_{gj} * Teacher_{lt}^{high} \\
& + \beta_5 Teacher_{lt}^{high} * Post_t + \beta_6 Teacher_{lt}^{high} * Treat_j + \beta_7 Teacher_{lt}^{high} * Treat_j * OverlapGrade_{gj} \\
& + \beta_8 Teacher_{lt}^{high} * Post_t * OverlapGrade_{gj} + \sum_z Teacher_{lt}^{z} + \beta_9 OverlapGrade_{gj} \\
& + X_{jt} + \tau_{cj} + \tau_{ct} + \epsilon_{ljt}
\end{aligned}
\tag{4}
$$

where $OverlapGrade_{gj}$ is an indicator of overlapped grades. β_h is the differential effect for high-quality teachers in overlapped grades [6].

[6] It is important to note that only a limited proportion of TPSs, approximately 16.55%, encompass both overlapped and non-overlapped grades. This may constrain the statistical power needed to detect significant effects of nearby charter school openings when utilizing the triple DID model. Given this limitation, the application of the triple DID methodology is confined to the teacher-level analysis, which has a greater number of observations compared to the school level.

3.2 Effects on Enrollment and School Composition

I first examine the effects of charter school openings on school enrollment in TPSs, with the findings illustrated in Figure 2. I find a significant decline in school enrollment in TPSs after a new charter school opened nearby [7]. This pronounced decline in enrollment is predominantly concentrated in grades facing competition (grades offered in both TPSs and the adjacent charter schools) [8].

Next, to investigate whether students and teachers disproportionately sort into charter schools, I examine the impacts of charter entry on student and teacher body composition in TPSs. Results are shown in Figure 3. I find a significant increase in the proportion of economically disadvantaged students in TPSs after charter entry, and negative effects on the average baseline scores of students remaining in TPSs, particularly in ELA classes. This evidence indicates that TPSs experience a disproportionate loss of economically advantaged students and high-achieving students to charter schools [9]. Regarding student racial composition, there is a significant increase in the proportion of Hispanic students while the proportions of White and Black students decrease after charter entry. These findings align with the results reported in the existing literature using North Carolina Data (Slungaard Mumma, 2022; Sorensen and Holt, 2020).

Panel (b) of Figure 3 presents estimates of the effects on teacher body composition in TPSs. I find no significant effects on the teacher composition in terms of race, education level, experience, and value-added [10]. This evidence suggests that TPSs are not losing or

[7] Table B.1 presents the estimated average effects of charter openings on school enrollment. According to Panel A, the total school enrollment in TPSs reduces by 11.20 on average and the enrollment in grades facing competition reduces by 8.29. Grades not in direct competition with charter schools do not exhibit a significant enrollment change.

[8] I find no significant evidence of pre-existing trends in the enrollment of TPSs exposed to nearby charter openings. Therefore, the observed negative impacts on TPS enrollment are unlikely to be attributable to pre-existing enrollment trends.

[9] In Appendix Figure C.2, I dissect the composition effects to show that changes in student body composition in TPSs following charter openings are driven by charter schools cream-skimming students from TPSs rather than the influx of new students.

[10] The average experience of teachers remaining in TPSs appear to increase, which aligns with the finding in Sorensen and Holt (2020), who also examine the effect of charter entry on the teacher composition in TPSs using the North Carolina data.

hiring teachers in a systematic way [11].

3.3 Effects on Student Academic Performance in TPSs

This section analyzes the effects of charter school openings on average Math and ELA test scores within TPSs, as well as on school proficiency rates—the share of students meeting or exceeding the proficiency threshold. The main findings are shown in Figure 4 [12]. Exposure to nearby charter schools leads to a statistically significant decrease in both the proficiency rate and average test scores in ELA among TPSs. Specifically, there is a decline of 0.9 percentage points in ELA proficiency rate, accompanied by a decrease of 0.018 standard deviations in the average standardized ELA test scores. In Math, the presence of proximate charter schools significantly decreases the average standardized test scores by 0.014 standard deviations. However, it does not lead to a notable decline in school proficiency rates [13].

[11] The course membership data from NCERDC records which teacher works in which school in each academic year. This information allows me to track the movement of teachers across schools and helps identify teachers who leave, stay, or are newly hired in TPSs each year. Table B.2 in the Appendix shows the estimated effects of charter openings on the characteristics of teacher leavers, stayers, newcomers. I find that for each type of teachers, charter openings have no significant impact on the average education level, teaching experience, and value-added. Two key caveats in identifying teacher leavers and newcomers warrant consideration. Firstly, the lack of teacher identification data in charter schools hinders tracking movements from TPSs to charter schools. Secondly, teacher departures from TPSs are defined as those who transition to a different school in the following academic year or those who are unobserved in the data. Newly hired teachers are those who moved from a different school in the previous year or were absent from data in the prior academic year. Importantly, teachers who are missing from the data for a given academic year may still be employed at the same school, leading to misclassification of leavers and newly hired teachers.

[12] Table B.3 provides the corresponding estimated coefficients and clustered standard errors.

[13] In other research using North Carolina data to examine the impact of nearby charter openings, the main effects on the quality of TPSs vary, from null impacts (Slungaard Mumma, 2022) to positive effects (Jinnai, 2014). Slungaard Mumma (2022) focuses on charter openings from 1997 to 2015, and the estimated impacts on test scores in Math and ELA are both negative, although not statistically significant. Jinnai (2014) investigates the effects of charter openings in the earlier stage of charter expansion in North Carolina, using data from 1997 to 2005. Given that the competitive effects of charters on TPSs' quality are sensitive to the nature of nearby charter schools, such as the quality level, geographic proximity, and curriculum (Cohodes and Parham, 2021; Gilraine et al., 2021; Cordes, 2018; Cremata and Raymond, 2014), my findings differ from Jinnai (2014), possibly because different charter schools entered the market in different stages of charter expansion.

3.4 Effects on Class Structure

This section presents novel evidence on how TPSs adjust the class structure in response to charter school competition, as illustrated in Figure 5 [14]. Compared with schools located more than 5 miles away from the new charter school, TPSs located within 5 miles of the new charter experience significant reductions in the number of classes and teachers in both ELA and Math after the new charter started to enroll students. On average, the number of Math classes in TPSs reduces by 1.024 (7.00%), and the number of ELA classes reduces by 1.174 (7.58%). TPSs exposed to charter entry also lose around 0.468 (5.34%) Math teachers and 0.582 (6.58%) ELA teachers, respectively. The loss of teachers translates into significant increases in the class size, the number of classes assigned to each teacher, and student-teacher ratio in TPSs. The average class size increases by 0.310 (1.63%) in Math and 0.321 (1.71%) in ELA. The number of classes per teacher increases by 0.099 (5.29%) in Math and 0.084 (4.31%) in ELA. Similarly, the student-teacher ratio (the number of students per teacher) increases by 1.834 (5.23%) in Math classes and increases by 1.528 (4.18%) in ELA classes [15].

3.5 Effects on Teacher-to-Student Allocation

This section conducts an in-depth analysis of the strategies employed by TPSs in reallocating teachers to students in response to the competitive pressures arising from nearby charter school openings. The analysis encompasses two key dimensions: firstly, whether TPSs engage in reallocation of teachers across different grades; and secondly, whether there are adjustments in the criteria governing the assignment of teachers to specific student groups.

[14] Table B.4 provides the corresponding estimated coefficients and clustered standard errors.

[15] As a placebo test, I examine the effects on overlapped grades and non-overlapped grades separately, and find that such significant impacts on class structure only concentrate on overlapped grades (results are shown in Figure C.3). Moreover, I use the triple DID model and the teacher-level data to check the robustness, results are shown in Table B.5. Estimates from the triple DID model provide consistent results: nearby charter openings increase the number of students and classes assigned to teachers.

3.5.1 Allocation of Teachers Across Grades

Table 3 presents the results on whether TPSs reallocate teachers across grades in response to charter school entry. The outcome variable is a binary indicator of whether teachers are reassigned to a different grade compared to the previous year. Overall, there is no evidence that TPSs reallocate teachers across grades following the introduction of a new charter school [16].

3.5.2 Allocation of Teachers Across Student Groups

In this section, I investigate the distribution of teachers among students, focusing on the composition of each teacher's class. Column (1) and (3) in Table 4 present the main findings. Post-charter school openings, teachers in the base group—those with below-average value-added scores, five or fewer years of experience, or no graduate degree—experience a significant decrease in the proportion of economically disadvantaged students they teach, along with a notable increase in their students' baseline academic performance. Nevertheless, charter entry has differential impacts on high-quality teachers, as evidenced by the positive and significant coefficient on the interaction term with the high-quality teacher indicator in Column (1), and the negative, significant coefficient on the interaction term in Column (3).

Using estimates from Table 4, Figure 6 plots the estimated effects of nearby charter openings for high-quality teachers and other less-qualified teachers respectively, with 95% confidence intervals. The figure indicates a significant reduction in average baseline scores for high-quality teachers' classes but a significant increase for other less-qualified teachers' classes. The fraction of economically disadvantaged students rises in high-quality teachers' classes (although not significant) but falls in other less-qualified teachers' classes. This suggests that TPSs strategically allocate more high-quality teachers to

[16] I plot the event study estimates using equation 3 to assess the pre-trends in teachers' grade change, and I find no evidence of a violation of parallel trends (results are shown in Figure C.6).

low-achieving and economically disadvantaged students after charter school entries. I examine the impacts on teacher-to-student allocation in ELA classes as well and results are shown in Table 4 and Figure 7. The reallocation pattern in ELA classes mirrors that observed in Math classes.

Confounding Effects from Teacher and Student Sorting: A key concern over the teacher-to-student allocation analysis is that observed changes in student characteristics assigned to teachers might result from overall shifts in teacher and student body composition rather than TPSs' strategic responses to charter entries. High-quality teachers may end up with more economically disadvantaged and low-achieving students after charter school openings because: (1) TPSs disproportionately lose economically advantaged and high-achieving students (see Figures 3 and C.2); and (2) in North Carolina, high-quality teachers are typically matched with high-achieving, economically advantaged students[17]—so when these students leave, they are replaced by relatively lower-achieving and more disadvantaged peers.

To confirm that the estimated effects are not due to changes in teacher and student composition post-charter entry, I employ two strategies. First, I examine the impact of charter openings on the overall teacher composition in TPSs, including the characteristics of teachers who leave, stay, or are newly hired. As shown in Figure 3 and Table B.2, there is no significant impact of nearby charter openings on teacher composition, indicating that TPSs do not systematically lose teachers.

Second, I analyze the variation in teacher-to-student allocation using students' percentile scores within their school, grade, and year, which are not affected by changes in overall school composition [18]. This approach captures the relative achievement level of students in each teacher's class by comparing them to their peers within the same school-

[17]Figure C.5 shows that high-achieving and economically advantaged students usually get above-average teachers, while their lower-achieving and economically disadvantaged peers get below-average teachers.

[18]Students are ranked in each school-grade-year cell according to their lagged test scores (baseline scores), and percentile scores are calculated accordingly.

grade-year cohort, rather than relying on absolute test scores. If there is no notable change in average percentile scores, it would suggest no change in the teacher allocation strategy, with high-quality teachers consistently receiving students with top percentile rankings and lower-quality teachers getting lower-ranked students. Conversely, significant shifts in these scores would indicate a strategic change in teacher allocation.

For evaluating the proportion of economically disadvantaged students in each teacher's class, percentile scores are not directly feasible due to the binary nature of this status. Instead, teachers are ranked within schools based on the fraction of economically disadvantaged students in their classes, and percentile scores are assigned. High-quality teachers are expected to maintain lower percentile scores, while low-quality teachers have higher scores. If the allocation strategy remains unchanged, no significant variation in teachers' percentile scores is expected.

Figure 6 presents the results and reveals a consistent teacher reallocation pattern: TPSs reallocate high-quality teachers to support lower-income and lower-achieving students in response to charter competition. Specifically, there is a significant decline in average percentile scores for high-quality teachers' classes and a significant increase for classes taught by other less-qualified teachers. Additionally, high-quality teachers are assigned a greater proportion of economically disadvantaged students (evidenced by a significant rise in the percentile score of economically disadvantaged student fractions), while less-qualified teachers are assigned fewer. I also use percentile scores within school-grade-year cells to evaluate student composition in ELA teachers' class and the results are presented in Figure 7. This figure exhibits a teacher-to-student allocation pattern analogous to that observed in the Math class.

Rationale Behind Strategic Teacher Reallocation: The reallocation of high-quality teachers to low-achieving and economically disadvantaged students may represent a strategic response by TPSs to counteract potential declines in school proficiency rates due to charter schools drawing away high-achieving students. Faced with the exodus of these

students, TPSs are concerned that a reduction in proficiency rates could damage their reputation and incur penalties within the school accountability framework. In response, TPSs have a compelling incentive to focus on students who are below the proficiency standard. This study explores whether TPSs prioritize these students by assigning high-quality teachers to those not yet proficient. The analysis utilizes percentile ranks (PR) of teachers within school-grade-year cells, based on the proportions of their students at each proficiency level [19].

The findings, illustrated in Figure 8, demonstrate that the presence of nearby charter school openings leads to high-quality teachers being assigned a greater proportion of students below the proficiency standard (students at proficiency level 1 and level 2) and fewer advanced students (students at proficiency level 3 and level 4). Conversely, low-quality teachers are assigned more advanced students and fewer below the proficiency standard. This pattern suggests that TPSs strategically allocate students below proficiency to high-quality teachers, likely as a response to increased competition and accountability pressures from the migration of high-achieving students.

Robustness of Findings: The robustness of these findings is tested using a triple DID model. Results are shown in Panel B of Table 4, which compares the estimates of the main DID model and the triple DID model. Most estimated coefficients are consistent across models, although the magnitudes of coefficients from the triple DID model are slightly smaller and the standard deviations are larger, which suggests potential issues with statistical power. Results from the triple DID models confirm that TPSs are more likely to assign high-quality teachers to economically disadvantaged and low-achieving students in response to charter openings.

[19] In 2014, North Carolina revised its proficiency standards, creating three distinct groups (proficiency levels 3, 4, and 5) instead of the previous two (proficiency levels 3 and 4). Post-2014, levels 4 and 5 are combined for classification purposes.

3.5.3 Teacher-Student Matching

In this section, I estimate the effects of charter openings on teacher-student matching based on gender, race, and teachers' comparative advantages in teaching different students in TPSs. Table 5 presents the results of the gender and racial match in Math and in ELA. Overall, the analysis finds that charter school openings have positive effects on both gender and racial matching between teachers and students, with a larger magnitude for racial matching. However, most of these effects are statistically insignificant except for the racial matching in Math [20].

Table 6 presents the results of teacher-student matching based on teachers' comparative advantages. It shows that charter school openings have negative effects on teacher-student matching—whether assessed by the fraction of students well-matched to teachers based on the comparative advantage indicator, or by the overall matching quality measure. However, most of these effects are statistically insignificant [21].

4 A Model of School Choice and School Competition

Motivated by the observed patterns of TPSs reallocating teachers in response to competition, I develop and estimate a structural model of school choice and competition. The novel aspect of this model is that it incorporates the teaching resources allocation on both the demand side as an attribute that students consider when selecting schools, and the supply side as a strategic variable that schools adjust in response to competition. Specifically, the school choice and competition model characterizes the following process:

[20] To ensure that the estimated effects are not influenced by changes in the gender or racial composition of teachers and students following charter school openings, I controlled for the gender and racial composition of teachers at the school level, as well as the gender and racial composition of students, to assess the robustness of the results. Charter openings only have a significantly positive impact on racial matching in math classes after controlling for the student and teacher racial composition at school.

[21] The estimated effects are robust after controlling for student and teacher composition at school level. One exception is Column (3), where I find significantly negative effects on the matching quality in Math classes. However, this estimated effect becomes insignificant after controlling for the fraction of economically disadvantaged students at school level and the fraction of Math teachers with comparative advantages in teaching economically disadvantaged students at school level.

Teacher Allocation Strategy: TPSs strategically adjust their teacher-to-student allocations to maximize their market share and overall school proficiency rates, while adhering to capacity constraints. This behavior reflects schools' responses to the competitive pressures introduced by the presence of charter schools.

Student Choice Behavior: Students choose schools to maximize their utility, which depends on several factors, including overall school quality, the availability of high-quality teachers, peer composition, and home-school distance. The model allows for heterogeneity in students' preferences based on race, baseline achievement level, and economic disadvantage status.

Equilibrium Outcomes: In equilibrium, TPSs make optimal decisions regarding teacher-to-student allocations, and students select schools that best meet their preferences. The resulting distribution of student achievement is realized based on the education production function, which incorporates the strategic interactions between schools and students.

4.1 Market Definition

Education markets are defined based on students' school choice sets and the scope of competition. In this paper, each school district is defined as an independent market $m \in 1, ..., M$ [22]. In North Carolina, students usually choose schools within their home districts, the school districts they reside in. Most school districts are defined based on county boundaries. Schools outside of home districts are available through residential relocation. Students can also take advantage of the open enrollment programs to transfer from home district to another school district. However, only students with unique hardship or children of an employee at the school are eligible for the open enrollment program in North Carolina. Thus I assume that the number of students choosing out-

[22] Market subscript is suppressed in this section to simplify exposition.

of-district schools is negligible if they do not move [23], and schools mainly compete for students with schools located in the same district [24].

4.2 Education Production Function

The education production function describes the relationship between teacher quality and student academic performance. Student i's proficiency level when they are taught by teacher l in school j in year t is denoted by $Proficiency_{iljt}$. Proficiency level depends on students' lagged score $Score_{ijt-1}$, whether teacher l is of high quality $Teacher_{lt}^{high}$, peer composition at school $Peer_{jt}$, student i's characteristics $X_{it}^{Student}$, teacher characteristics $Teacher_{lt}^{z}$, and school characteristics X_{jt}^{School}. I allow the effect of having a high-quality teacher on student proficiency level differs between high-achieving and low achieving students by adding the interaction between $Teacher_{lt}^{high}$ and the indicator of being a high-achieving student D_{it}^{Ach} [25].

$$\begin{aligned} Proficiency_{iljt} = \alpha Score_{ijt-1} + \beta_l Teacher_{lt}^{high} + \beta_{diff} Teacher_{lt}^{high} * D_{it}^{Ach} + \varphi Peer_{jt} \\ + X_{it}^{Student} + Teacher_{lt}^{z} + X_{jt}^{School} + StuFE_i + \epsilon_{it} \end{aligned} \tag{5}$$

$Peer_{jt}$ include the fractions of White students and the fraction of economically disadvantaged students in the school. $X_{it}^{Student}$ include economically disadvantaged status, indicator of English language learners, indicator of gifted students, indicator of students with disability, age, days of absence, and grade. $Teacher_{lt}^{z}$ consists of three teacher quality variables indicated by z: education level (measured by whether teacher l has a graduate degree), years of teaching experience, and teacher value-added. X_{jt}^{School} include school

[23] According to the American Community Survey 2013-2017, 86.45% of students on average live in the same residence as one year ago, and 6.45% students on average live in the same county as in the last year. Therefore, the proportion of students moving across markets is also relatively small.

[24] This paper assumes that private schools are not considered by students who have already enrolled in public schools.

[25] D_{it}^{Ach} equals 1 if student i is proficient in year $t-1$.

enrollment, student composition by gender, race, English language learner status, gifted status, and disability status, average days of absence, average age, and teacher composition by education level, experience, and average value-added. $StuFE_i$ represents student fixed effects.

I also estimate the education production function using students' standardized test scores as the dependent variable. This model tells how teacher quality affects students' test scores. I use this model in the counterfactual analysis to evaluate the effects of alternative school choice policy on student test scores.

4.3 Student Demand Model

The objective of the student demand model is to characterize students' school choices based on evaluating the utilities they could obtain from different schools. In each market, a student i, defined by D_i, chooses which school to attend based on school characteristics. $D_i = (D_i^{Poor}, D_i^{Ach}, D_i^{White})$ represent observed student characteristics and they include indicators of poor students D_i^{Poor} [26], high-achieving students D_i^{Ach}, and white students D_i^{White}.

I use a discrete choice model to project students' utilities U_{ijt} from school j. Students' utilities from school j depend on school quality $Proficiency_{jt}^S$, teacher-to-student allocation regime $Quality_{jt}^T$, schools' peer composition $Peer_{jt} = (White\%_{jt}, Poor\%_{jt})$, home-school distance $distance_{ijt}$, and unobserved school characteristics ξ_{jt}. $Proficiency_{jt}^S$ is measured by school proficiency rate. Teacher-to-student allocation regime $Quality_{jt}^T$ is measured by the fraction of high-achieving students assigned to high-quality teachers, defined by the combination of above-average value-added scores, possession of a graduate degree, and more than five years of teaching experience. $White\%_{jt}$ represents the proportion of white students in school j in year t and $Poor\%_{jt}$ is the proportion of poor students.

[26] Poor students are the same with the economically disadvantaged students in the reduced-form analysis and these students are eligible for free or reduced-price lunch.

I assume students' belief about the student body composition at school is consistent with the realized student body composition at school.

Importantly, this model allows students to have differential tastes for school characteristics based on observed student characteristics, which is realized through interacting school characteristics with student observed characteristics D_i. Specifically, I allow students' taste for school quality and the teacher-to-student allocation regime differ by students' baseline achievement level D_i^{Ach}. For instance, high-achieving students prefer schools that assign a larger fraction of high-achieving students to high-quality teachers, while low-achieving students dislike such schools. Students may also have own group preference hence I allow students' preference for peer composition to differ by students' own race and poverty level.

$$U_{ijt} = \underbrace{\beta_i^{PR} Proficiency_{jt}^{S}}_{School\ Quality} + \underbrace{\beta_i^{QT} Quality_{jt}^{T}}_{Allocation\ Regime} + \underbrace{\bar{\beta}^{Dist} Distance_{ijt}}_{Home-school\ Distance} + \underbrace{\beta_i^{Peer} Peer_{jt}}_{Peer\ Composition} + \xi_{jt} + \varepsilon_{ijt} \tag{6}$$

$$\beta_i^k = \bar{\beta}^k + D_i * \beta_d^k, \quad \text{where } k = PR, QT, Peer$$

4.4 School Supply Model

School j's problem is to choose a teacher-to-student allocation regime $\boldsymbol{Quality_{jt}^{T}}$ to maximize market share and school proficiency rate, subject to capacity constraints. Following Mehta (2017) and Fu and Mehta (2018), I assume schools maximize both market share and school proficiency rate. In North Carolina, school enrollment directly influences school revenues, as funding is allocated on a per-student basis. Concurrently, public schools face accountability pressures from state policies that assess academic performance through school proficiency rates. These proficiency rates serve as a key metric in school report cards, which publicly convey the overall quality of schools to parents and students. Under this dual pressure, schools must attract and retain students while simultaneously

improving proficiency rates to maintain and enhance their public standing. The utility function for school j is defined as:

$$\pi_{jt} = \max_{Quality_{jt}^{T}} \{Share_{jt} + \omega_{jt} Proficiency_{jt}\} \tag{7}$$

Schools' utilities π_{jt} come from the weighted average of market share, $Share_{jt}$, and the proficiency rate, $Proficiency_{jt}$. I normalize the weight on $Share_{jt}$ into 1, so the coefficient ω_{jt} shows the relative weight compared to $Share_{jt}$.

Schools choose the teacher-to-student assignment regime $Quality_{jt}^{T} \in [0, 1]$. These decisions are made within the limits of capacity constraints, specified as follows:

$$\begin{cases} N_{jt}^{stu_hach} * Quality_{jt}^{T} \leq N_{jt}^{stu} * \lambda_{jt} \\ N_{jt}^{stu} * \lambda_{jt} - N_{jt}^{stu_hach} * Quality_{jt}^{T} \leq N_{jt}^{stu} - N_{jt}^{stu_hach} \end{cases} \tag{8}$$

In school j in year t, the student body comprises N_{jt}^{stu} students, among which $N_{jt}^{stu_hach}$ are classified as high-achieving. The share of students assigned to high-quality teachers in school j is denoted by λ_{jt}. The capacity constraint requires: 1) the total number of high-achieving students assigned to high-quality teachers ($N_{jt}^{stu_hach} * Quality_{jt}^{T}$), must not exceed the total number of seats in high-quality teachers' classes ($N_{jt}^{stu} * \lambda_j$); 2) the remaining seats in high-quality teachers' classes for low-achieving students ($N_{jt}^{stu} * \lambda_j - N_{jt}^{stu_hach} * Quality_{jt}^{T}$), must not exceed the number of low-achieving students in the school ($N_{jt}^{stu} - N_{jt}^{stu_hach}$) [27].

I rewrite equation 8 to derive the minimum and maximum values of $Quality_{jt}^{T}$ (de-

[27] In the counterfactual analysis, I assume the share of students assigned to high-quality teachers (λ_{jt}) remains stable in school j before and after nearby charter openings. As is shown in Table B.4, nearby charter openings do not have differential impacts on the number of students assigned to teachers with different quality levels. Moreover, I do not find significant evidence of teacher composition change in TPSs after nearby charter openings.

noted by $\underline{Quality_{jt}^T}$ and $\overline{Quality_{jt}^T}$), and also limit $Quality_{jt}^T \in [0,1]$:

$$\underbrace{max\{0, \quad \frac{N_{jt}^{stu} * \lambda_j - N_{jt}^{stu} + N_{jt}^{stu_hach}}{N_{jt}^{stu_hach}}\}}_{\underline{Quality_{jt}^T}} \leq Quality_{jt}^T \leq \underbrace{min\{1, \quad \frac{N_{jt}^{stu} * \lambda_j}{N_{jt}^{stu_hach}}\}}_{\overline{Quality_{jt}^T}}$$

The unconstrained first-order condition with respect to $Quality_{jt}^T$ is specified below:

$$\frac{\partial share_{jt}}{\partial Quality_{jt}^T} + \omega_{jt} \frac{\partial Proficiency_{jt}}{\partial Quality_{jt}^T} = 0$$

where $\frac{\partial share_{jt}}{\partial Quality_{jt}^T}$ can be recovered using the estimates in the demand function and $\frac{\partial Proficiency_{jt}}{\partial Quality_{jt}^T}$ can be recovered using the estimates in the education production function[28].

It is unclear how schools will choose $Quality_{jt}^T$ under different scenarios. On the one hand, schools may prefer a higher $Quality_{jt}^T$ (assigning a higher fraction of high-achieving students to high-quality teachers) to improve market share, if high-achieving students have a stronger taste for teacher quality than low-achieving students. On the other hand, schools may prefer a lower $Quality_{jt}^T$ (assigning a higher fraction of low-achieving students to high-quality teachers) in order to improve school proficiency rates.

5 Model Estimation and Results

This section introduces the model estimation methods and the estimation results. I also discuss the identification of the key parameters in the school competition model.

5.1 Estimation of Education Production Function

I use the value-added model to estimate the effects of teacher quality and peer composition on student test scores in equation 5. I assume that for a given student, conditional on the rich set of student-level, grade-level, and school-level time-variant characteristics,

[28] Appendix E.1 provides more details.

being assigned to a high-quality teacher is independent from ϵ_{it}. In addition, I employ instrumental variables to address the omitted variable bias arising from potential correlations between peer composition and unobserved, time-variant quality factors. Section 5.4 introduces instrumental variables in detail.

5.2 Estimation of Student Demand Model

In the estimation of student demand model, I use the method of moments estimator following Berry et al. (2004), which is a standard application of structural model estimation from the empirical Industrial Organization literature. The estimation uses aggregated moments that fit the school market shares predicted by the model to the actual market shares observed in the data, micro moments that fit the characteristics of schools each group of students is predicted to choose to actual choices observed from the data, and instrumental variables moments.

I rewrite the student utility function (equation 6) to decompose it into the utility common to all students δ_{jt} and the differential utilities across students σ_{ijt}.

$$U_{ijt} = \delta_{jt} + \sigma_{ijt} + \varepsilon_{ijt} \tag{9}$$

$$\begin{aligned}\delta_{jt} = {} & \bar{\beta}^{PR} proficiency^{S}_{jt} + \bar{\beta}^{QT} Quality^{T}_{jt} + \bar{\beta}^{Dist} Distance_{ijt} + \bar{\beta}^{Peerwhite} Peerwhite_{jt} \\ & + \bar{\beta}^{Peerpoor} Peerpoor_{jt} + \xi_{jt}\end{aligned} \tag{10}$$

$$\begin{aligned}\sigma_{ijt} = {} & (\beta_d^{PR} * D_i^{Ach}) Quality^{S}_{jt} + (\beta_d^{QT} * D_i^{Ach}) Quality^{T}_{jt} + (\beta_d^{Peerwhite} * D_i^{White}) Peerwhite_{jt} \\ & + (\beta_d^{Peerpoor} * D_i^{poor}) Peerpoor_{jt} + \varepsilon_{ijt}\end{aligned} \tag{11}$$

The parameters in the delta function (equation 10), including $\bar{\beta}^{PR}$, $\bar{\beta}^{QT}$, $\bar{\beta}^{Dist}$, $\bar{\beta}^{Peerwhite}$, $\bar{\beta}^{Peerpoor}$, represent students' common tastes for corresponding school characteristics. In equation 11, parameters interacted with student characteristics D_i represent the differential tastes for the corresponding school characteristics. In the delta function, I decompose

the unobserved school characteristics ξ_{jt} into three parts: the time-invariant characteristics ξ_j, the common shocks ξ_t, and the period-specific demand shock $\Delta\xi_{jt}$. I add school fixed effect effects to control for ξ_j and year fixed effects to control for ξ_t.

The GMM problem is specified below and all the unknown parameters are collectively denoted by Π.

$$\min_{\Pi} q(\Pi) = \bar{g}(\Pi)' W \bar{g}(\Pi)$$

where $q(\Pi)$ is the GMM object, W is the weighting matrix, and $\bar{g}$ is a vector of moments. In the GMM estimation, a nonlinear optimizer finds the $\hat{\Pi}$ that minimizes $q(\Pi)$.

I.Aggregate Moments for Market Shares: Aggregated moments fit the market shares predicted by the model to the actual market shares observed in the data. These aggregated moments are used for estimating $\boldsymbol{\delta}$. The moment condition is formalized as below:

$$\bar{g}_1 = Share^{observed} - Share^{estimated}$$

II.Instrumental Variables Moments: I use three sets of instrumental variables including the demographics of residents in the neighborhood, teacher salary, and the availability of college graduates and teacher certification programs. Section 5.4 introduces instrumental variables in detail. The instrumental variables moments express the orthogonality between the period specific demand shock $\Delta\xi$ and the instruments Z.

$$\bar{g}_2 = Z' \Delta\xi$$

III.Micro Moments: Micro moments are constructed with student-level data, and they fit the average school characteristics each group of students (defined by observed student characteristics D_i) chooses predicted by the model to the data. Specifically, the estimation chooses the parameters to fit the expected values of the interactions between D_i and the characteristics of the chosen schools ($Proficiency^S_{jt}$, $Quality^T_{jt}$, and $Peer_{jt}$) to the corre-

sponding values in the data.

$$\bar{g}_3 = \begin{bmatrix} E[Proficiency^S * D_i]^{observed} - E[Proficiency^S * D_i]^{estimated}(\Pi) \\ E[Quality^T * D_i]^{observed} - E[Quality^T * D_i]^{estimated}(\Pi) \\ E[White\% * D_i]^{observed} - E[White\% * D_i]^{estimated}(\Pi) \\ E[Poor\% * D_i]^{observed} - E[Poor\% * D_i]^{estimated}(\Pi) \end{bmatrix}$$

5.3 Estimation of School Supply Model

On the supply side, I need to estimate the relative weight ω_{jt} that schools put on school proficiency rate. I assume ω_{jt} is log-normally distributed, then $\tilde{\omega}_{jt} = ln(\omega_{jt})$ follows a normal distribution $\tilde{\omega}_{jt} \sim N(\mu, \sigma^2)$, where μ is the mean and σ is the standard deviation. I estimate μ and σ using the maximum likelihood method, where parameter estimates maximize the probability of observing $\tilde{\omega}$. Appendix E.2 introduces the estimation details.

5.4 Identification

The estimation of model parameters encounters the challenge of endogeneity. In estimating student demand for schools, period-specific demand shocks that are visible to students but not researchers could lead to biased parameter estimates if these shocks are correlated with school quality, teacher quality, and peer composition. To address this issue, I employ an instrumental variable (IV) design. The ideal instruments should exhibit correlation with school quality, availability of high-quality teachers, and peer composition, while remaining independent of period-specific demand shocks, denoted as $\Delta\xi_{jt}$.

Instruments for Peer Composition

I employ neighborhood demographics as instruments for school peer composition, following Ferreyra et al. (2018) and Allende (2019). These demographics serve as relevant instruments because schools typically draw students from their local communities, resulting in a correlation between the racial composition and income levels of these com-

munities and the student demographics of the schools. Specifically, I use the proportion of white residents and median household income at the census tract level, sourced from ACS 5-year estimates, to construct these instruments. To mitigate concerns about students sorting into neighborhoods in response to period-specific demand shocks—which could violate the orthogonality assumption—I use demographic estimates from the past five years as instruments for the current year's school peer composition.

Instruments for School Quality and the Availability of High-quality Teachers

To address the issue of endogeneity in school quality and the availability of high-quality teachers, which can be correlated with short-term demand shocks and unobservable school characteristics, I construct two sets of instrumental variables. The first set exploits the exogenous variation in teacher base salary across years and across teacher groups in North Carolina. Teacher salaries are strongly correlated with school quality and the availability of high-quality teachers due to two primary factors. First, teacher salaries constitute a significant portion of schools' instructional inputs and are associated with student test scores, as indicated by prior research (Loeb and Page, 2000; Figlio and Kenny, 2007; Hendricks, 2014). Second, variations in teacher salaries across years and among teachers with different education levels and experience can impact who enters and exits the teaching profession, as well as teacher effort.

Public school teachers in North Carolina are paid on a state salary schedule according to educational levels and experience [29]. The state salary schedule is set and approved annually by the state and the general assembly, with annual pay raises varying both across years and across teacher groups [30]. Figure 9 plots the variation in teacher base salary over time and across different teacher groups based on teaching experience and education level.

[29] The state salary schedule sets a minimum pay while local school districts can approve additional funds to supplement the base salary to account for variances such as geographic location, market conditions or school demographics.

[30] Adjustments in salary schedule are influenced by the state's economic conditions, fiscal health, revenue projections, and political priorities. When the state government, through the legislative process, decides to increase this base pay, it typically allocates additional state funds to cover the increased cost.

To construct the instrumental variables, I interact the salary in year t for teachers with e years of experience with the percentage of teachers with e years of experience in school j in year $t-1$, which effectively captures the treatment intensity [31]. Using the teacher composition from year $t-1$ prevents potential bias from schools strategically hiring or firing teachers in response to salary changes. I generate these interactions separately for teachers with master's degrees and bachelor's degrees [32].

The second set of instrumental variables utilizes data on the availability of graduates with master's degrees or higher from higher education institutions. The presence of teachers with graduate degrees in a school correlates with the volume of such graduates and the proximity to higher education institutions, especially those offering teacher certification programs. Schools near colleges and universities with increasing graduate enrollment and teacher certification programs are more likely to employ and attract teachers with advanced degrees. Using IPEDS data, I construct variables representing distance-weighted graduate-level enrollment from two years prior and the average distance to colleges and universities offering teacher certification programs.

Appendix E.3 presents the first-stage for the endogenous school characteristics which confirms the relevance of the instrumental variables.

5.5 Model Estimation Results

This section presents the results from estimating the education production function, the student demand model, and the school supply model.

[31] I categorize years of teaching experience into 4 groups: less than 5 years, 5-9 years, 10-14 years, and 15 years or more.

[32] These instrumental variables constructed using variation in teacher base salary are relevant only in school districts where this base salary is binding. In districts where teacher salaries already exceed the state-set base level, state-level salary variations will not impact these salaries, unless school districts adjust teacher salary along with the state.

5.5.1 Estimation of Education Production Function

First, I use student-level data to estimate Equation 5, and results are shown in Table 7. I find that high-quality teachers positively affect students' proficiency levels and standardized test scores. The effects on proficiency levels are heterogeneous, depending on the students' lagged proficiency levels. Specifically, students who were not proficient in the previous year benefit more from having a high-quality teacher compared to students who were proficient. Similarly, there is also heterogeneity in the effects of high-quality teachers on standardized test scores. In the IV regression, I also find that the proportions of white students and poor students at school have significantly negative impacts on students' proficiency levels and standardized test scores[33].

5.5.2 Estimation Results of Demand and Supply Models

Panel A of Table 8 shows the estimates of student utility function. Estimates have expected signs. On average students prefer schools located close to their homes and schools with a lower proportion of poor students. Regarding the heterogeneity, high-achieving students exhibit more pronounced preferences for school quality and the availability of high-quality teachers compared with low-achieving students. I also find that students have own group preference: white students have a stronger preference for the fraction of white students at school while poor students have a stronger preference for the fraction of poor students at school.

Panel (a) of Figure 10 plots the distributions of market share elasticity with respect to the teacher-student allocation regime, specifically the proportion of high-achieving students allocated to high-quality teachers, before and after the introduction of charter schools. The market share of all schools increases with a higher proportion of high-achieving students assigned to high-quality teachers, as high-achieving students value the availability of high-quality teachers more significantly. The introduction of charter

[33] First-stage estimates are shown in Appendix Table B.8.

schools shifts the market share elasticity distribution rightward, indicating that schools' market shares become more responsive to the teacher-student allocation regime.

Panel (b) of Figure 10 presents the distributions of school proficiency rate elasticity with respect to the teacher-student allocation regime. It shows that proficiency rates decline as the proportion of high-achieving students assigned to high-quality teachers increases, attributed to the higher effectiveness of high-quality teachers in improving the proficiency levels of low-achieving students. The entry of charter schools increases the sensitivity of proficiency rates to the teacher-student allocation regime, shifting the elasticity distribution leftward. This indicates that TPSs experience a greater decline in proficiency rates when they allocate a higher fraction of high-achieving students to high-quality teachers under competitive pressure, aligning with empirical evidence that TPSs tend to assign more high-quality teachers to low-achieving students in response to competition.

The elasticity distributions of market share and proficiency rate highlight the complex dynamics between teacher allocation strategies, school enrollment, and school performance in a competitive educational environment. The rightward shift in market share elasticity suggests TPSs are incentivized to allocate more high-quality teachers to high-achieving students to retain them. Conversely, the leftward shift in proficiency rate elasticity indicates that allocating high-quality teachers to low-achieving students is more optimal for enhancing school quality. This ambiguity underscores the complex decision-making processes schools face, balancing between improving market share and overall proficiency in a competitive environment.

Panel B of Table 8 presents the supply model estimates. The estimated mean of $\tilde{\omega}$ is 1.589 (hence the mean weight TPSs put on school proficiency rate is 4.899), which demonstrates that schools value both school proficiency rate and market share. In the literature, Mehta (2017) also models public schools' utilities using data from North Carolina and he also finds that public schools both academic performance and school enrollment size.

6 Counterfactual Analysis of Charter Expansion Policy

In this section, I use the estimated school choice and competition model to evaluate counterfactual school choice policies and to decompose the effects of charter school openings on student achievements. The primary focus is on the expansion of the charter school sector, a policy question of significant interest. In 2011, North Carolina passed a landmark education reform bill that effectively lifted the cap on the number of charter schools. To evaluate the impact of this policy, I follow Gilraine et al. (2023) and remove all charter schools established after 2011 from the market. This counterfactual analysis examines equilibrium outcomes regarding the allocation of high-quality teachers, student performance, and the implications for educational equity and efficiency, under the premise that the cap on charter schools had not been lifted in 2011.

In this analysis, I restrict my sample to markets exposed to charter entries after 2011 and exclude the 36 newly opened charter schools after 2011 from the choice sets. I then solve for the optimal teacher-to-student assignment regime and the resulting student achievement in TPSs. A critical aspect of this analysis is the focus on the academic performance of "student stayers"—those who did not transition to new charter schools following the 2011 policy change. This focus allows for a deeper understanding of the competitive effects of school choice policy.

Table 9 and Figure 11 present the results. The column labeled "YES+Reallocation" shows outcomes observed following the implementation of the charter school cap-lifting policy, while the column "No" displays the outcomes had the cap not been lifted in 2011. The charter expansion policy reduces the fraction of high-achieving students assigned to high-quality teachers in TPSs by 2.054 percentage points. Consequently, high-achieving students experience a decline in test scores by 0.065 standard deviations and a reduction in proficiency rates by 1.669 percentage points due to reduced access to high-quality teachers. In contrast, low-achieving students benefit from the policy, with the fraction of low-achieving students assigned to high-quality teachers increasing by 4.098 percentage

points, proficiency rates increasing by 0.572 percentage points, and test scores rising by 0.035 standard deviations. This improvement is attributed to the increased allocation of high-quality teachers to low-achieving students, consistent with the results from reduced-form analysis.

I then assess the economic significance of the impacts on low-achieving students by benchmarking these effects with the estimates of the causal effect of teacher quality in (Chetty et al., 2014b), following the methodology of Gilraine et al. (2023)[34]. The estimated increase in low-achieving students' standardized test scores after the charter expansion policy translates to a 1.325 percentage point increase in college attendance probability and a 2.10% increase in lifetime earnings. Given that the mean present value of lifetime earnings in the US population is approximately $522,000 (Chetty et al., 2014b), the charter expansion policy causes a $10,962 increase in lifetime earnings [35].

These findings have significant implications for educational equity and efficiency. The improvements among low-achieving students indicate that the charter expansion policy narrows achievement gaps, enhancing educational equity. However, the negative impacts on high-achieving students suggest the policy is efficiency-neutral, as the gains for disadvantaged students come at the expense of high-achieving students. This trade-off highlights the complex dynamics in balancing equity and efficiency in educational policy.

Policy Effects Decomposition: The Roles of Student Sorting and Teacher Reallocation

The equilibrium impact of the charter expansion policy on student achievement is driven by two main forces: student sorting into schools and the strategic reallocation of teachers by TPSs in response to competitive pressure. In the second counterfactual analysis, I decompose the policy's effects into those arising from student sorting (via peer

[34] Chetty et al. (2014b) find that a one standard deviation increase in teacher value-added raises test scores by 0.13 standard deviations of the student test score distribution on average across grades and subjects. A one standard deviation improvement in teacher value-added in a single grade raises the probability of college attendance at age 20 by 0.82 percentage points, and it raises annual earnings by 1.3 percent.

[35] When students are exposed to nearby charter openings for 6 years (from grade 3 to grade 8), the increase in college attendance probability is equal to $\frac{0.035*0.82*6}{0.13} = 1.325$ percentage points. The increase in earnings is equal to $\frac{0.035*0.013*6}{0.13} = 2.10\%$.

effects) and those resulting from teacher reallocation (via the competition channel). By disallowing TPSs from reallocating teachers and permitting only student sorting under the charter expansion policy, this approach removes the competition channel, thereby isolating the equilibrium effects attributable solely to student sorting among schools.

Results shown in the "YES" column indicate that, in the absence of strategic teacher reallocation, neither high-achieving nor low-achieving students experience a significant change in academic achievement due to deteriorated peer quality. Combined with the findings from the first counterfactual analysis, this evidence suggests that TPSs' strategic resource reallocation plays a major role in the impacts of charter expansion on incumbent schools, disproportionately benefiting low-achieving students.

Efficiency Gains from Improving Teacher-student Matching

Is there scope to enhance the allocative efficiency of charter school expansion policies and benefit students across the board? I address this question by performing a counterfactual analysis that allows schools to improve the teacher-student matching based on teachers' comparative teaching advantages. Specifically, I identify teachers who excel at teaching high-achieving (low-achieving) students by comparing their value-added scores in teaching high-achieving versus low-achieving students. I then match these teachers to high-achieving (low-achieving) students to the greatest extent possible.

I perform this new counterfactual analysis that improves teacher-student matching, given the teacher-student allocation regime chosen by TPSs after the lifting cap policy. The results, shown in the column "YES+Matching", indicate that improving teacher-student matching is an efficacious approach to realizing efficiency gains. Enhancing matching increases high-achieving students' test scores by 0.01 standard deviation, while the performance gains for low-achieving students are even more pronounced, at 0.022 standard deviations. Thus, integrating teachers' comparative teaching advantages into reallocation strategies can help mitigate learning losses among high-achieving students and significantly boost test scores for low-achieving students.

7 Conclusion

Improving the quality of the public school system is a critical policy issue in the United States. School choice initiatives, such as charter schools, are often proposed to introduce competitive forces into the education market and stimulate TPSs to raise quality. This belief motivates empirical research on the competitive effects of school choice on the academic performance of neighboring schools, but results have been mixed overall (Gill and Booker, 2008; Ridley and Terrier, 2018; Slungaard Mumma, 2022).

The competitive effect of school choice depends significantly on how schools respond to competition. This paper opens up the black box of TPSs to examine their responses to increased competition, particularly focusing on the allocation of teaching resources and the resulting heterogeneous effects on different students. Additionally, it develops and estimates a structural model of school choice and competition to explore the equilibrium effects of alternative policy designs that might achieve greater equity and efficiency gains.

Results show that the openings of nearby charter schools lead to substantial reductions in student enrollment and the number of teachers within TPSs. In response, TPSs restructure classes by reducing the number of classes, leading to significant increases in class sizes and student-teacher ratios. To cope with challenges from charter schools, TPSs adopt compensation strategies by assigning more high-quality teachers to disadvantaged students, including those from economically disadvantaged backgrounds and those with lower academic achievement records. Additionally, nearby charter openings do not significantly improve racial matching, gender matching, or matching based on teachers' comparative teaching advantages in TPSs.

In the counterfactual analysis, the policy of lifting caps on charter schools in North Carolina in 2011 increased access for low-achieving students to high-quality educators. This policy shift resulted in a 4.098 percentage point increase in the proportion of low-achieving students assigned to these high-quality teachers, leading to notable improvements in the proficiency rates and test scores of low-achieving students. Further decom-

position of the policy effects indicates that TPSs' resource reallocation strategy plays a major role in the impacts of charter expansion. The estimated increase in low-achieving students' standardized test scores after the charter expansion policy translates into a 1.325 percentage point increase in college attendance probability and a 2.10% increase in lifetime earnings.

To assess whether the allocative efficiency of charter school expansion policies can be improved, I conduct a counterfactual analysis that enables schools to enhance teacher-student matching based on teachers' comparative advantages. The findings indicate that optimizing teacher-student matching is an effective strategy for achieving efficiency gains, resulting in improved test scores for both high-achieving and low-achieving students.

The findings of this study have significant policy implications, particularly concerning equity and efficiency in education. The evidence suggests that charter expansion policies can improve educational outcomes for low-achieving students by reallocating high-quality teachers, thereby narrowing achievement gaps and promoting equity. However, this comes at the expense of high-achieving students, indicating an efficiency-neutral impact. Policymakers should consider strategies that optimize teacher-student matching based on comparative advantages to enhance overall efficiency and ensure that the benefits of charter school expansion are distributed more equitably across all student groups.

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Tables

Table 1: Descriptive Comparison between Charter Schools and Traditional Public Schools

	(1) Charter	(2) TPS	(3) Difference
Panel A: School Characteristics			
Enrollment	449.42	618.11	168.69***
Urban Area%	57.13	40.02	-17.11***
Panel B: Student Composition			
Economically Disadvantaged%	30.83	54.42	23.60***
White%	54.66	51.38	-3.29***
Black%	31.16	27.85	-3.31***
Hispanic%	6.17	13.67	7.50***
Asian%	2.16	2.25	.09
Panel C: Student Academic Performance			
Proficiency Rate Math	.65	.63	-.02***
Proficiency Rate ELA	.69	.63	-.06***
Math Test Scores	.10	-.00	-.10***
ELA Test Scores	.22	-.01	-.22***

Notes: This table reports the differences in means of school and student characteristics between charter schools and traditional public schools. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2: Effects of charter openings on the quality of TPSs

	Proficiency Rate		Average Test Scores	
	(1)	(2)	(3)	(4)
	ELA	Math	ELA	Math
Treat*Post	-.009***	.001	-.018***	-.014**
	(.003)	(.004)	(.006)	(.007)
Lagged scores ELA	.015	-.016	-.019	-.088
	(.023)	(.019)	(.082)	(.084)
Lagged scores Math	.069***	.086***	.199***	.228***
	(.011)	(.014)	(.054)	(.036)
N	81024	81024	81029	81029

Notes: This table reports the estimated effect of charter school openings on the proficiency rates and average test scores in TPSs. The regressions use school-level data. In each regression, I control for school quality (measured by the average lagged test scores in Math and ELA at the school level), school by cohort fixed effects, cohort by year fixed effects, and linear time trend at the school level. Each regression is weighted by the school enrollment size; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Effects of charter openings on the allocation of teachers across grades

	(1) ELA	(2) Math
Treat*Post	.005	.000
	(.008)	(.008)
Treat*Post*High Quality	.021	.014
	(.019)	(.020)
N	260259	273316

Notes: This table reports the estimated effect of charter school openings on whether TPSs reallocate teachers across grades. The outcome variable is the indicator of whether the teacher is in a different grade than the last year. The regressions use teacher-level data and control for school quality measured by lagged average test scores in Math and ELA, and teacher quality measured by years of teaching experience, education level (whether having a graduate degree), and teacher value-added. All regressions include school-by-cohort fixed effects and cohort-by-year fixed effects. Robust standard errors clustered at school level are reported in parenthesis; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: Effects of charter openings on teacher-student allocation

	Econ Disadvantaged %	Percentile of Econ Disadvantaged %	Average Baseline Score	Average of Students' Baseline Percentile Scores
	(1)	(2)	(3)	(4)
Panel A: DID Model				
Math				
Treat*Post	-.913**	-.265	.017*	.433**
	(.426)	(.431)	(.010)	(.218)
Treat*Post*High Quality	1.181	3.167*	-.082***	-2.280***
	(.808)	(1.824)	(.030)	(.832)
N	282006	282006	240163	240163
ELA				
Treat*Post	-.738*	-.633	-.003	.190
	(.436)	(.428)	(.009)	(.199)
Treat*Post*High Quality	1.082	5.393***	-.090***	-2.494***
	(.817)	(1.786)	(.025)	(.736)
N	287649	287649	245066	245066
Panel B: Triple DID Model				
Math				
Treat*Post*Overlap*High Quality	.916	2.223	-.068**	-1.904**
	(.845)	(1.889)	(.032)	(.886)
ELA				
Treat*Post*Overlap*High Quality	.817	5.141***	-.080***	-2.253***
	(.862)	(1.893)	(.027)	(.778)

Notes: This table reports the estimated effects of charter school openings on the the characteristics of students assigned to different teachers in TPSs. Panel A reports the estimates using the DID and Panel B reports the estimates using the triple DID model. The regressions use teacher-level data. The first column shows the effects on the proportion of economically disadvantaged students among all students taught by each teacher; the second column shows the effects on teachers' percentile score of the fraction of economically disadvantaged students. The third column shows the effects on the average baseline scores in Math/ELA among all students taught by each teacher, while the fourth column shows the effects on the average of their students' baseline percentile scores. The regressions control for school quality measured by lagged average test scores in Math and ELA, school composition measured by the lagged fraction of economically disadvantaged students, and teacher quality measured by years of teaching experience, education level (whether having a graduate degree), and teacher value-added All regressions include school-by-cohort fixed effects, grade fixed effects, and cohort-by-year fixed effects. Robust standard errors clustered at school level are reported in parenthesis; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Effects of charter openings on teacher-student Matching

	Math		ELA	
	(1)	(2)	(3)	(4)
Panel A: Matching by Gender				
Treat*Post	.001	.002	-.000	.001
	(.002)	(.001)	(.002)	(.001)
Student composition	NO	YES	NO	YES
Teacher composition	NO	YES	NO	YES
N	366415	366415	358902	358902
Panel B: Matching by Race				
Treat*Post	.006	.009**	.003	.006
	(.004)	(.004)	(.004)	(.004)
Student composition	NO	YES	NO	YES
Teacher composition	NO	YES	NO	YES
N	359430	359430	352335	352335

Notes: This table reports the estimated effect of charter school openings on the teacher-student matching in TPSs. The regressions use teacher-level data. In each column, I control for school quality measured by lagged average test scores in Math and ELA, school composition measured by the lagged fraction of economically disadvantaged students, and teacher quality measured by years of teaching experience, education level (whether having a graduate degree), and teacher value-added. In column (2) and column (4), I further control for the racial composition of teachers and students at the school level. All regressions include school-by-cohort fixed effects, grade fixed effects, and cohort-by-year fixed effects. Robust standard errors clustered at school level are reported in parenthesis; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Effects of charter openings on teacher-student Matching

	Value-Added by Econ Disadvantaged Status				Value-Added by Achievement Level			
	Well-Matched Students%		Total Value of Match		Well-Matched Students%		Total Value of Match	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Math								
Treat*Post	-.005	-.005	-.003*	-.003	-.002	-.002	-.001	-.001
	(.004)	(.004)	(.002)	(.002)	(.003)	(.003)	(.002)	(.002)
Student composition	NO	YES	NO	YES	NO	YES	NO	YES
Teacher composition	NO	YES	NO	YES	NO	YES	NO	YES
N	244825	244825	274328	273752	255805	255799	284269	283743
Panel B: ELA								
Treat*Post	.004	.002	-.000	-.001	-.002	-.002	-.003	-.003
	(.005)	(.005)	(.003)	(.003)	(.003)	(.003)	(.002)	(.002)
Student composition	NO	YES	NO	YES	NO	YES	NO	YES
Teacher composition	NO	YES	NO	YES	NO	YES	NO	YES
N	236804	236804	265477	264698	249763	249757	277703	277291

Notes: This table reports the estimated effect of charter school openings on the teacher-student matching in TPSs. The regressions use teacher-level data. In each column, I control for school quality measured by lagged average test scores in Math and ELA, school composition measured by the lagged fraction of economically disadvantaged students, and teacher quality measured by years of teaching experience, education level (whether having a graduate degree), and teacher value-added. In column (2), column (4), column (6), and column (8), I further control for teachers and students composition at the school level. Column (2) and column (4) control for the fraction of economically disadvantaged students at school and the fraction of teachers good at teaching economically disadvantaged students; Column (6) and column (8) control for the fraction of high-achieving students at school and the fraction of teachers good at teaching high-achieving students. When the outcome is the total value of the match, I also control for school-level average value-added in teaching economically advantaged and disadvantaged students in Column (3) and (4), and control for school-level average value-added in teaching high-achieving and low-achieving students in Column (7) and (8). All regressions include school-by-cohort fixed effects, grade fixed effects, and cohort-by-year fixed effects. Robust standard errors clustered at school level are reported in parenthesis; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: Education Production Function Estimates

	Proficiency Level in Math		Test Scores in Math	
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Teacher Characteristics				
High Quality	.046***	.046***	.080***	.080***
	(.001)	(.001)	(.006)	(.002)
High Quality*Lagged Proficiency	-.017***	-.016***	-.015***	-.014***
	(.002)	(.002)	(.005)	(.002)
School Characteristics				
Poor%	.007	-.257***	-.008	-.412***
	(.004)	(.023)	(.026)	(.030)
White%	.130***	-.049***	.029	-.213***
	(.005)	(.015)	(.023)	(.020)
Lagged test scores	YES	YES	YES	YES
Lagged test scores^2	YES	YES	YES	YES
Student characteristics	YES	YES	YES	YES
Other School characteristics	YES	YES	YES	YES
Student FE	YES	YES	YES	YES
N	1,691,497	1,684,558	1,692,943	1,685,998

Notes: This table shows the estimates in the education production function and estimated coefficients on selected variables are reported. The regressions use student-level data and control for student fixed effects. Standard errors are clustered at student level; *** p<0.01, ** p<0.05, * p<0.1

Table 8: School Choice and Competition Model Estimates

Panel A: Demand			
	Parameter	Coeff.	Std Err.
School Proficiency	$\bar{\beta}^{PR}$	0.669	0.672
School Proficiency x High-achieving	β_d^{PR}	5.352***	0.061
Avail. High-quality Teachers	$\bar{\beta}^{QT}$	-0.029	1.048
Avail. High-quality Teachers x High-achieving	β_d^{QS}	0.330***	0.021
Peer Poor %	$\bar{\beta}^{Peerpoor}$	-9.330***	1.931
Peer Poor % x Poor	$\beta_d^{Peerpoor}$	3.951***	0.044
Peer White%	$\bar{\beta}^{Peerwhite}$	-2.775	3.400
Peer White% x White	$\beta_d^{Peerwhite}$	3.548***	0.044
Distance	$\bar{\beta}^{Dist}$	-0.222	0.155
Observations (Student-years)			1,105,159
Panel B: Supply			
	Parameter	Coeff.	Std Err.
Mean of $\tilde{\omega}$	μ	1.589***	0.019
SD of $\tilde{\omega}$	σ	1.780***	0.014
Observations (School-years)			9,529

Notes: *** p<0.01, ** p<0.05, * p<0.1.

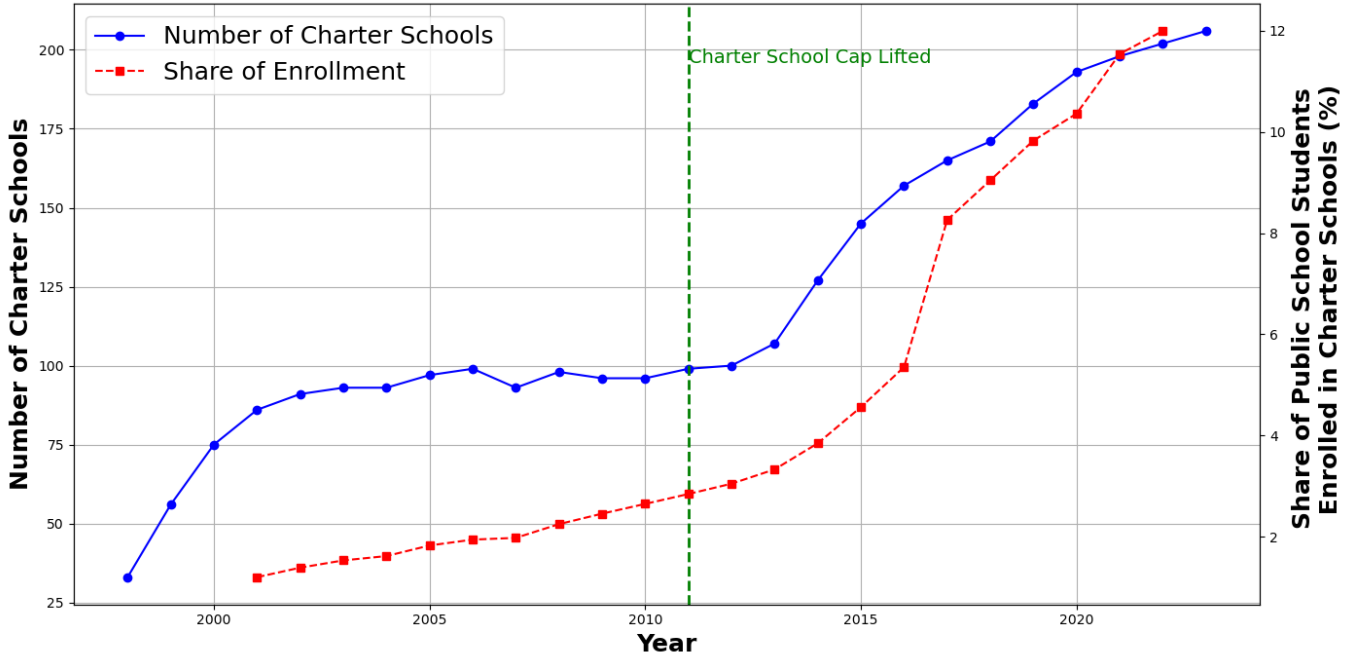
Table 9: Counterfactual: Lift cap policy on charter schools

	Lift Cap on Charters			
	No	YES	YES + Reallocation	YES + Matching
Panel A: Teacher-student assignment choices				
% High-achieving students assigned to high-quality teachers	30.299	30.299	28.245	28.245
% Low-achieving students assigned to high-quality teachers	23.245	23.245	27.343	27.343
Panel B: Proficiency Rates				
High-achieving students	84.129	84.158	82.460	-
Low-achieving students	17.536	17.564	18.108	-
Average	54.587	54.687	53.217	-
Panel C: Test Scores				
High-achieving students	0.676	0.677	0.611	0.621
Low-achieving students	-0.743	-0.743	-0.708	-0.686
Average	0.046	0.048	0.019	0.028

Notes: This table shows the equilibrium outcomes for different student groups under different counterfactual scenarios. The column labeled "YES+Reallocation" displays the outcomes observed from the data following the implementation of the lifting cap policy. In column "No", I present the outcomes if the cap on charter schools had not been lifted in 2011. In column "YES", I disallow TPSs from reallocating teachers to students, allowing only student sorting under the charter expansion policy. In the column labeled "YES+Matching", I allow schools to improve the teacher-student matching, given the teacher-student allocation regime TPSs choose after the implementation of the lifting cap policy.

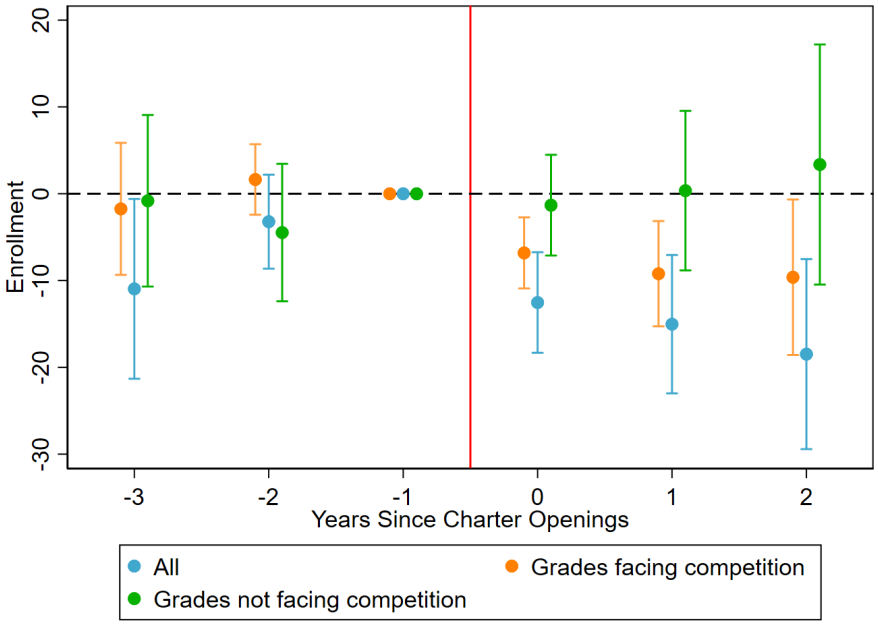
Figures

Figure 1: Trend in the Number of Charters and Share of Charter Enrollment



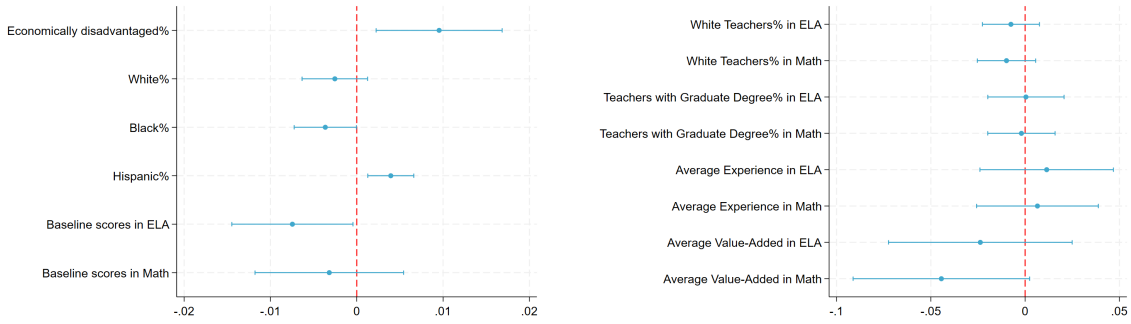
Notes: This figure shows the substantial growth in the number of charter schools and the share of public school students that enroll in charter schools since 1998.

Figure 2: The effects of charter openings on enrollment in TPSs



Notes: This figure shows the estimated effects of charter openings on total school enrollment, enrollment in grades facing competition from charter schools (grades served in both the traditional public school and the new charter school nearby), and enrollment in grades not facing competition in TPSs. I use the event study model specified in equation 3. Treated schools are those located within 5 miles of the new charter school. All regressions include school-by-cohort fixed effects, cohort-by-year fixed effects, and school-level linear time trend. Point estimates are displayed along with their 95% confidence intervals. Standard errors are clustered at the school level. The base period is 1 year prior to the charter openings.

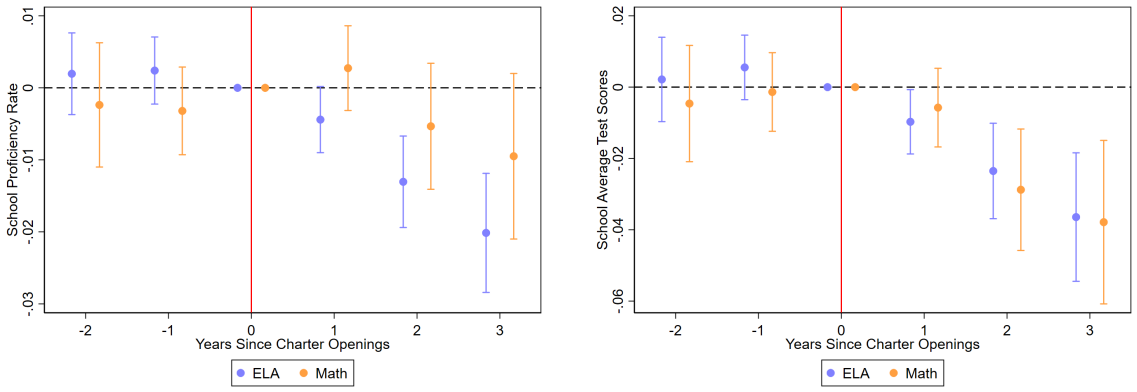
Figure 3: The effects of charter openings on school body composition in TPSs



(a) Student Composition (b) Teacher Composition

Notes: Panel (a) of this figure shows the estimated effects of charter openings on student body composition in TPSs, including the proportion of economically disadvantaged students, white students, black students, hispanic students, and the average Math and ELA baseline scores of students who are left in TPSs. Panel (b) of this figure shows the estimated effects of charter openings on teacher body composition in TPSs, including the proportion of white teachers, the proportion of teachers with graduate degrees, the average teaching experience, and the average value-added in Math and ELA. The unit of the teaching experience is decade in this figure. In each regression, I control for school quality (measured by the average lagged test scores in Math and ELA at the school level), school by cohort fixed effects, cohort by year fixed effects, and linear time trend at the school level. I plot the point estimate and the 95% confidence intervals for each regression. Standard errors are clustered at the school level.

Figure 4: The effects of charter openings on school proficiency rate and average test scores in TPSs

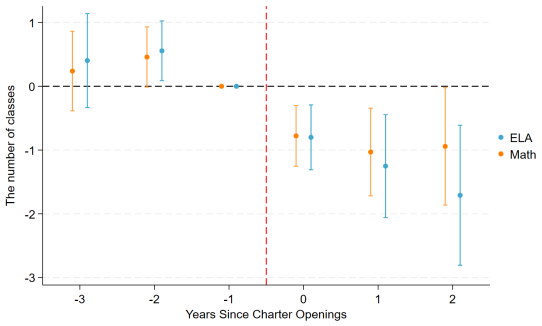


(a) School Proficiency Rate

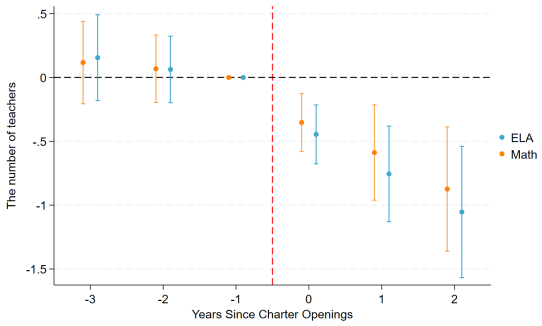
(b) Average Test Scores

Notes: Panel (a) of this figure shows the estimated effects of charter openings on school proficiency rate in TPSs. Panel (b) of this figure shows the estimated effects of charter openings on average test scores in TPSs. In each regression, I control for baseline school quality (measured by the average lagged test scores in Math and ELA at the school level), school by cohort fixed effects, cohort by year fixed effects, and linear time trend at the school level. I plot the point estimate and the 95% confidence intervals for each regression. Standard errors are clustered at the school level.

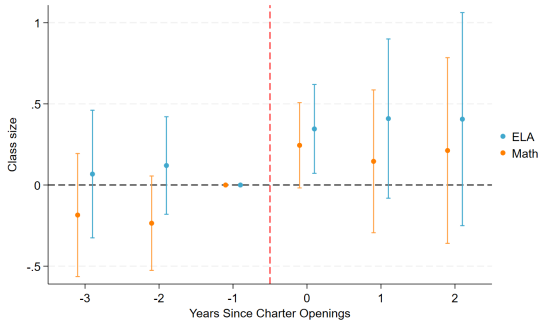
Figure 5: The effects of charter openings on class structure in TPSs



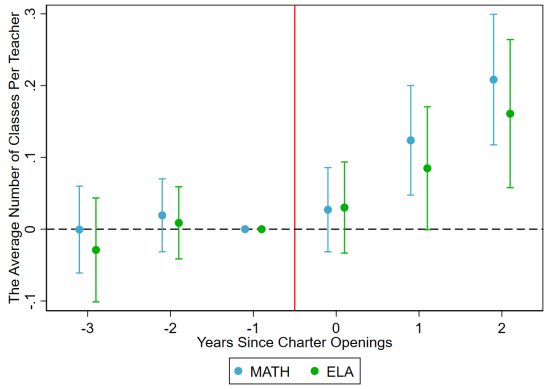
(a) The number of classes



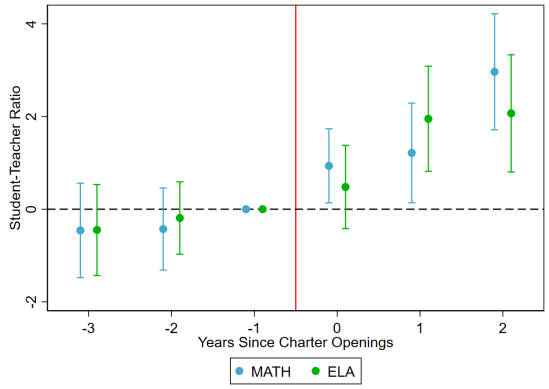
(b) The number of teachers



(c) Class size



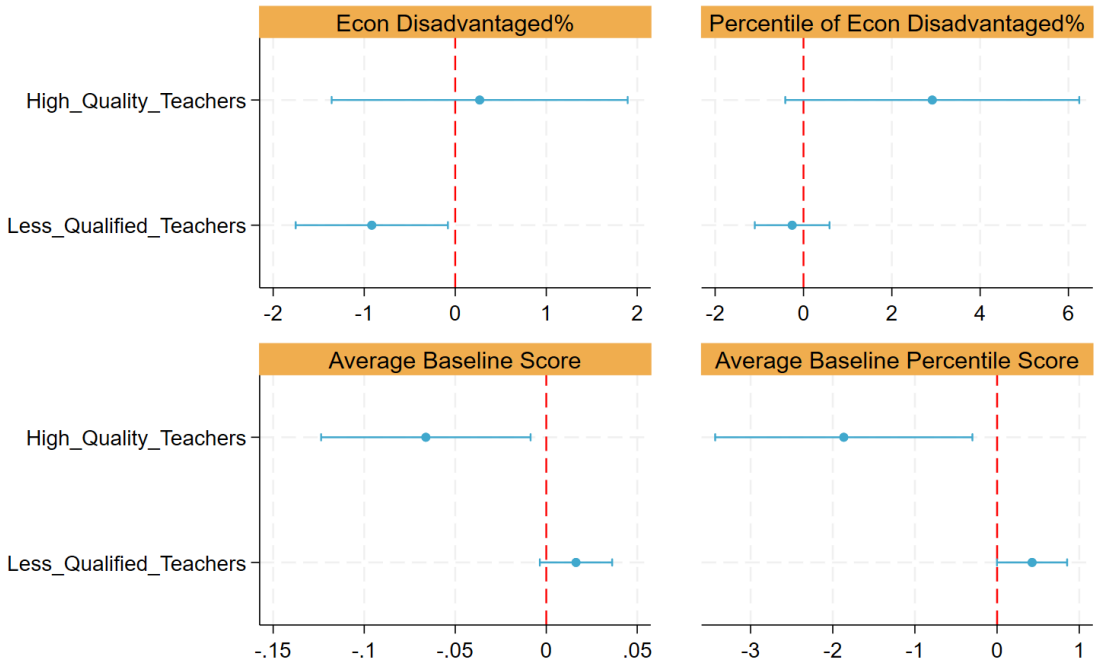
(d) The average number of classes per teacher



(e) Student-teacher ratio

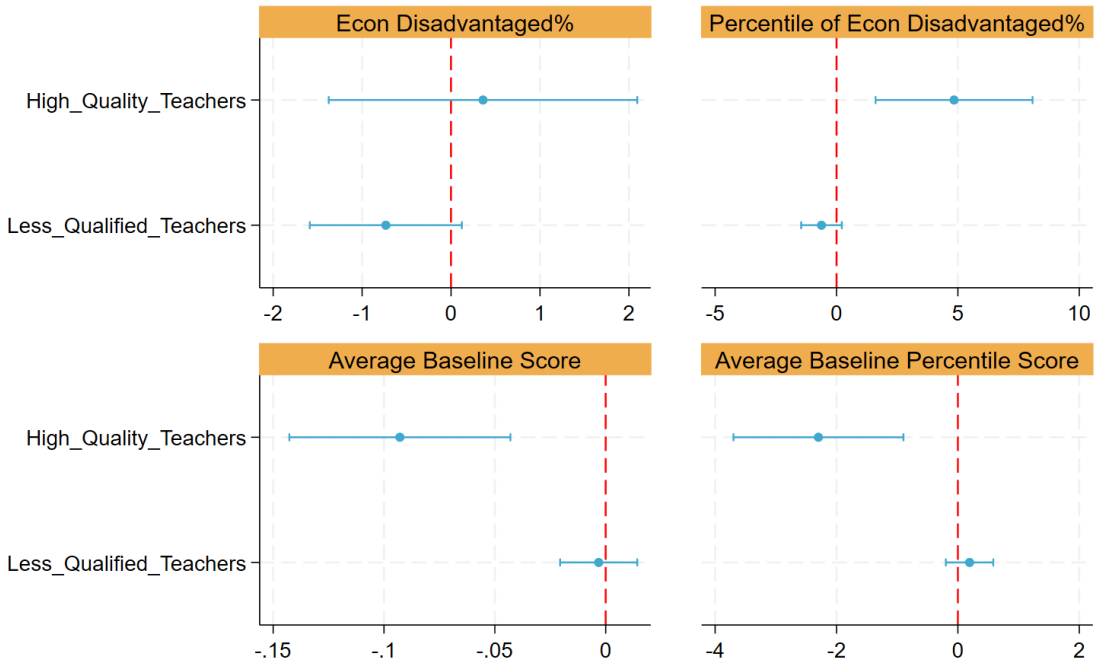
Notes:This figure plots the estimated effects of charter openings on the number of classes, the number of teachers, class size, the average number of classes per teacher, and student-teacher ratio in TPSs, using the event study model specified in equation 3. Figures (a), (b), and (c) use school level data and I control for school quality (measured by the average lagged test scores in Math and ELA at the school level), school by cohort fixed effects, cohort by year fixed effects, and linear time trend at the school level. Figures (d) and (e) use teacher level data and I control for school quality, school composition measured by the lagged fraction of economically disadvantaged students, teacher quality measured by teaching experience (centered), education level (whether having a graduate degree), and teacher value-added, school by cohort fixed effects, grade fixed effects, and cohort by year fixed effects. I plot the point estimate and the 95% confidence intervals for each regression. Standard errors are clustered at the school level.

Figure 6: Effects of charter openings on student composition in Math teachers' classes



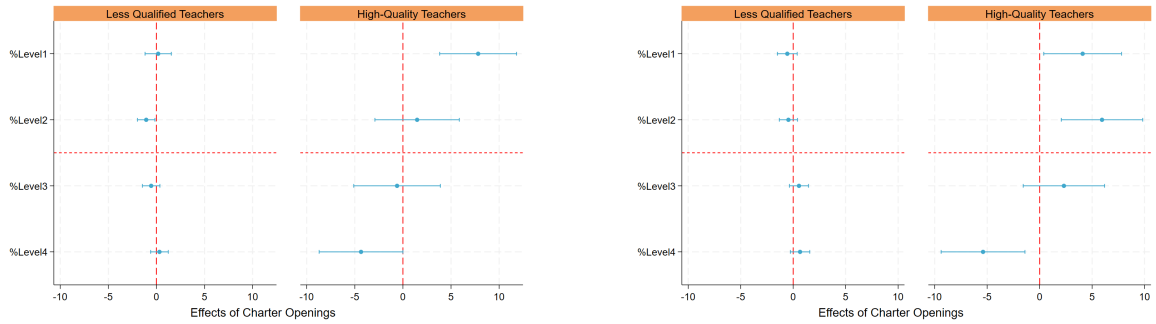
Notes: This figure plots the estimated effects of nearby charter openings on the student composition separately for high-quality and less qualified teachers in Math. The regressions use teacher-level data and control for school quality measured by lagged average test scores in Math and ELA, school composition measured by the lagged fraction of economically disadvantaged students, and teacher quality measured by years of teaching experience, education level (whether having a graduate degree), and teacher value-added. All regressions include school-by-cohort fixed effects, grade fixed effects, and cohort-by-year fixed effects. I plot the point estimate and the 95% confidence intervals. Standard errors are clustered at the school level.

Figure 7: Effects of charter openings on student composition in ELA teachers' classes



Notes: This figure plots the estimated effects of nearby charter openings on the student composition separately for high-quality and less qualified teachers in ELA. The regressions use teacher-level data and control for school quality measured by lagged average test scores in Math and ELA, school composition measured by the lagged fraction of economically disadvantaged students, and teacher quality measured by years of teaching experience, education level (whether having a graduate degree), and teacher value-added. All regressions include school-by-cohort fixed effects, grade fixed effects, and cohort-by-year fixed effects. I plot the point estimate and the 95% confidence intervals. Standard errors are clustered at the school level.

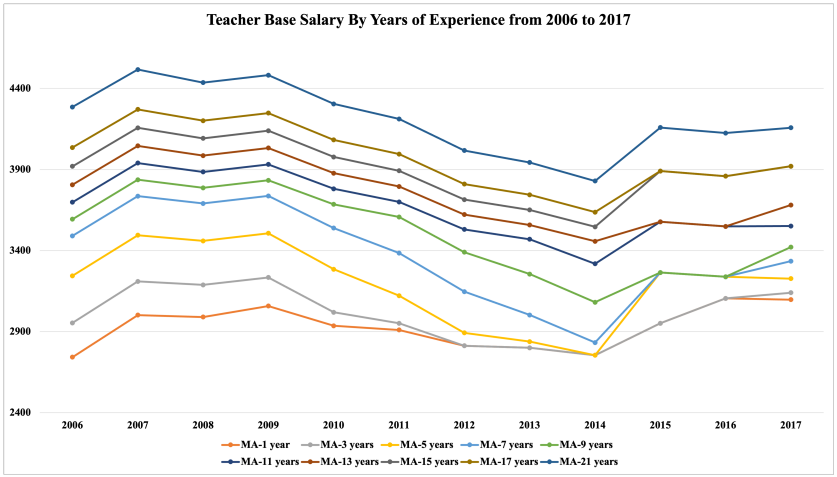
Figure 8: Effects of charter openings on student composition by proficiency levels



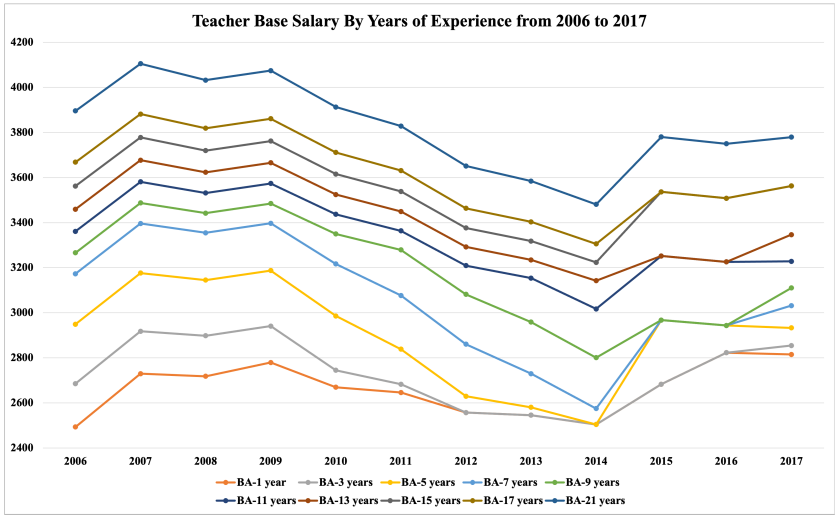
(a) Math (b) ELA

Notes: This figure presents the estimated impacts of charter school openings on the composition of students, categorized by proficiency levels, within each teacher's class. The analysis employs teacher-level data for the regressions. The dependent variables in this analysis are the percentile ranks (PR) of teachers, determined by the proportions of their students at respective proficiency levels. Treated schools are those located within 5 miles of the new charter school. The regressions control for school quality measured by lagged average test scores in Math and ELA, school composition measured by the lagged fraction of economically disadvantaged students, and teacher quality measured by years of teaching experience, education level (whether having a graduate degree), and teacher value-added. All regressions include school-by-cohort fixed effects, grade fixed effects, and cohort-by-year fixed effects. Robust standard errors clustered at school level are reported in parenthesis; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 9: Teacher Base Salary by Education Levels and Experience from 2006 to 2017



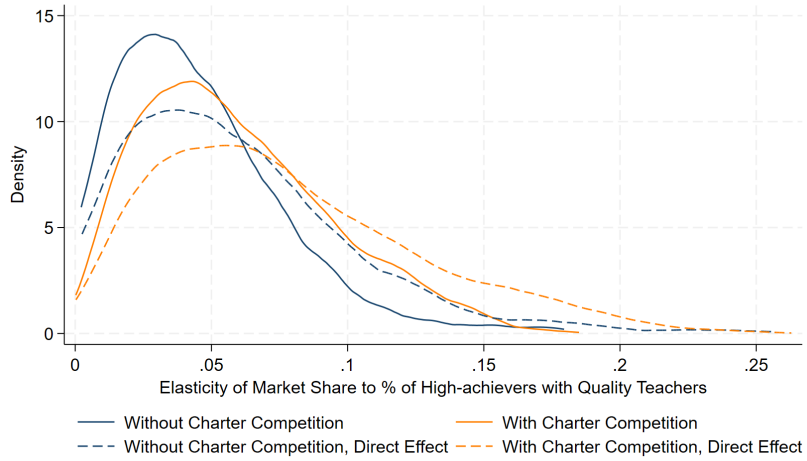
(a) Teachers with Master's Degrees



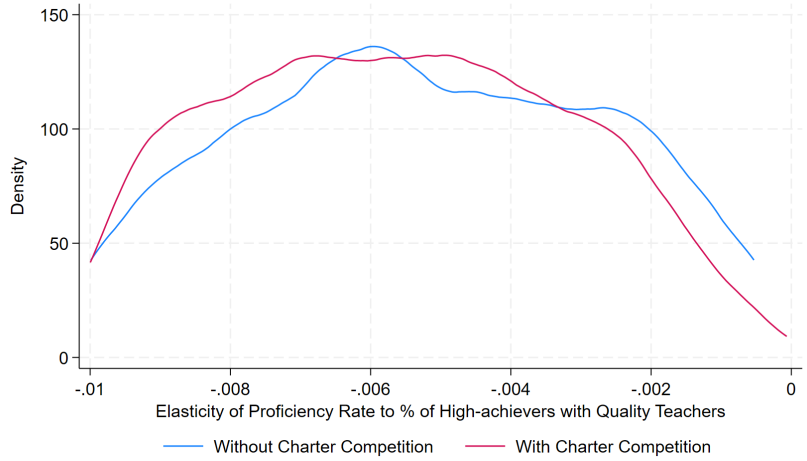
(b) Teachers with Bachelor's Degrees

Notes: This figure shows the variation in teacher base salary (monthly) across years and across teachers with different education levels and years of teaching experience. Salaries are adjusted for inflation, with 2005 as the base year.

Figure 10: Elasticity with respect to the fraction of high-achievers with high-quality teachers



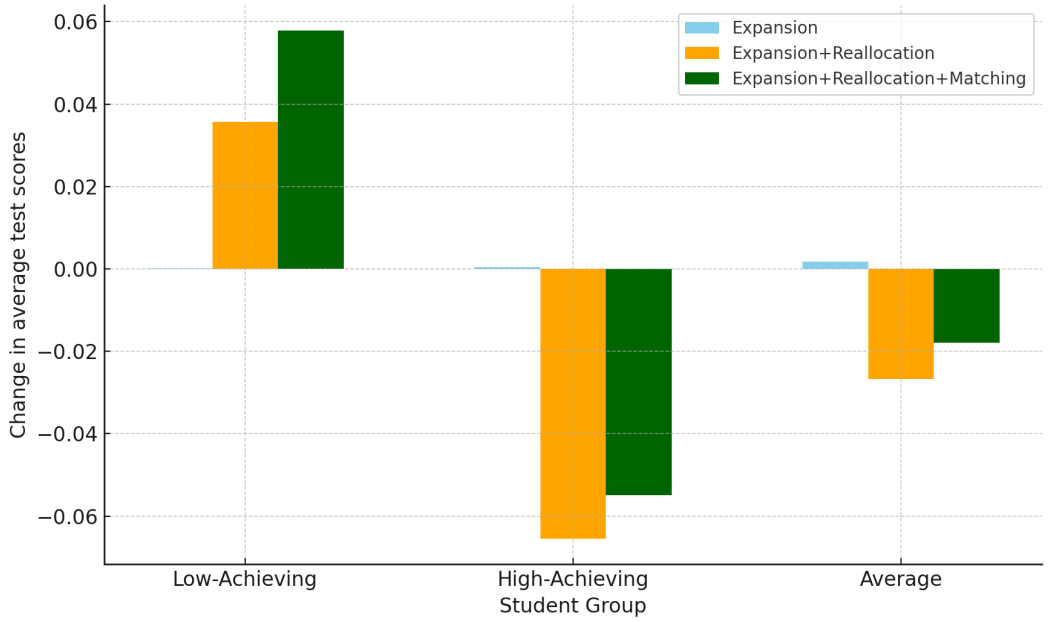
(a) Market Share



(b) Proficiency Rate

Notes: This figure shows the elasticity of market share and the elasticity of proficiency rate with respect to the fraction of high-achievers with high-quality teachers respectively, before and after charter openings. The solid line shows the overall effect of the teacher-student allocation regime on market share, including both the direct effect (students' preference over allocation regime) and the indirect effect (impact on school proficiency rates), whereas the dashed line represents solely the direct effect of the teacher-student allocation regime on market share.

Figure 11: Counterfactual: Changes in Test Scores



Notes: This figure shows the change in test scores for different student groups under different counterfactual scenarios. The baseline is the scenario when the charter expansion policy has not been implemented.

Online Appendix

A Measurement of Teacher Value-Added

Teacher value-added is a commonly used measure of teacher quality and it reveals teachers' effects on improving students' test scores. Numerous schools and districts have adopted teacher value-added approach in the evaluation of teachers (Chetty et al., 2014a).

In this paper, I follow the method proposed in Chetty et al. (2014a) to estimate each teacher's value-added. Basically, the estimation method in Chetty et al. (2014a) predicts teachers' value-added based on the average test scores of each teacher's students, while controlling for a rich set of student-level characteristics including lagged test scores and demographics, and teacher-level, classroom-level, and school-level characteristics. It allows for the drifting of teacher value-added across time given that test scores in more recent years are better predictors of teachers' effects on test scores. After controlling for a rich set student-, class-, and school-level characteristics, the estimated teacher value-added is unbiased predictor of teacher quality.

The estimator of teacher value-added in each year is constructed in three steps. First, I residualize the student test scores by estimating equation 12 using student-level data. A_{it}^{*} is student i's test score in Math or ELA in year t. $\boldsymbol{X}_{it}$ is a vector of student characteristics including gender, grade, race, age, economically disadvantaged status, English language learner indicator, indicator of being identified as a gifted student, indicator of being identified as a student with disability, and the number of absence days. I also controlled for teacher education level and experience, classroom fixed effects, school fixed effects, and time-variant school or school-grade characteristics including the enrollment size, racial composition of students, the fraction of economically disadvantaged students, the fraction of students with disability, the fraction of gifted students, the fraction of English language learners, and the average number of absence days among students. α_r is the teacher fixed effects.

$$A_{it}^{*} = \rho \boldsymbol{X}_{it} + \alpha_r + \epsilon_{it} \tag{12}$$

The test score residual for student i in year t is A_{it}:

$$A_{it} = A_{it}^{*} - \hat{\rho} \boldsymbol{X}_{it} \tag{13}$$

In the second step, I estimate the best linear predictor of mean test score residuals in classes taught by teacher r based on the mean test score residuals in classes taught by

teacher r in prior years. Specifically, I run an ordinary least square regression of the mean test score residuals in classes taught by teacher r, $\bar{A}_{rt}$, on the mean test score residuals in classes taught by teacher r in prior years, A_r^{-t}.

In the final step, I use the resulting coefficients ψ in Step 2 to predict teacher r's value-added in year t, $\hat{u}_{st}$:

$$\hat{u}_{st} = \sum_{t0}^{t-1} \psi' \bar{A_s^{-t}} \tag{14}$$

Figure C.1 in the Appendix show the density distribution of teacher value-added in ELA and Math respectively. The estimated teacher value-added basically follows a bell-shaped distribution in both ELA and Math. Teacher value-added in schools with above-median average test scores is higher than that in schools with below-median average test scores.

B Robustness Analysis of Distance Radius Choice

In the literature on the competitive effects of charter schools on TPSs, there is no consensus regarding what constitutes a nearby charter school, and researchers employ different distance radii to define treatment schools and control schools. The distance radius used in studies ranges from 2 miles (Slungaard Mumma, 2022), 2.5 miles (Gilraine et al., 2021), 5 miles (Gilraine et al., 2021), 10 miles (Jackson, 2012), and 20 miles (Jackson, 2012; Gilraine et al., 2023).

In this section, I explore the sensitivity of the main results to the choice of distance radius. I adopt a 10-mile radius, following Sorensen and Holt (2020). This choice is motivated by the average commuting distance in the two largest cities in North Carolina, Charlotte and Raleigh, which is approximately 9.7 miles and 8.5 miles, respectively (Sorensen and Holt, 2020). Using the 10-mile radius helps ensure that relevant charter openings are not overlooked and prevents the attenuation of the effects of charter openings.

Moreover, when defining treated schools using the 5-mile radius, schools located between 5 miles and 10 miles from the new charters are classified as part of the control group. This setup could introduce bias in the estimated effects of charter openings if schools situated between 5 miles and 10 miles from the new charter schools are also influenced by the presence of those new charters. To address this issue, I repeat the main analysis but exclude the schools located between 5 miles and 10 miles from the new charter schools in the control group. I then examine how the estimated effects vary under this

modified approach.

Enrollment: The estimated impacts on school enrollment demonstrate robustness. The estimated effects on school enrollment excluding schools located between 5 miles and 10 miles in the control group are presented in Panel B of Table B.1. The findings employing a 10-mile radius to define the treatment group are presented in Panel C of Table B.1. These two groups of analysis further confirm the detrimental effects of charter school openings on TPS enrollment.

Student and Teacher Composition: The estimated effects on student and teacher composition are robust to using the 10-mile radius in defining the treatment groups, as shown in Figure C.4. The estimated effects are also robust to excluding control schools located between 5 miles and 10 miles of the new charters in the control group.

Student Academic Performance: The estimated impacts on both the average test scores and proficiency rates in Math and ELA demonstrate robustness. This robustness is affirmed upon the exclusion of TPSs situated within a 5 to 10-mile radius of the new charter schools from the control group and upon employing a 10-mile radius criterion to define the schools treated in the analysis. Results are shown in Table B.3

Class Structure: I repeat the analysis of how charter entry affects the class structure in TPSs but exclude the schools located between 5 miles and 10 miles of the new charters in the control group. I also use the 10-mile radius to define treated schools. Results are shown in Table B.4. The main findings of the impacts on class structure remain consistent and robust, despite the observation that most effect sizes obtained using the 10-mile radius criterion are somewhat smaller compared to those derived using the 5-mile radius. This variation in effect sizes is likely attributable to a diminishing intensity of the charter schools' impact on TPS class structures, as the distance from these charter schools increases.

Teacher to Student Allocation: Results of the robustness analysis of how charter openings affect the allocation of teacher across grades are presented in Table B.6. Results of the impacts on the allocation of teacher across student groups are shown in Table B.7. The main findings remain robust in these two alternative analyses.

C Decomposition of Student Enrollment Shifts in TPSs

Changes in student body composition in TPSs following charter openings may be driven by charter schools cream-skimming students from TPSs or the influx of new students. To dissect these composition effects, I further categorize students into three groups: those who remain in the same TPS before and after charter openings (stayers), those who newly

enroll in the TPS after charter openings (newcomers), and those who leave the TPS after charter openings (switchers). I then assess the effects of charter openings on the composition of these three groups separately.

Results for student composition by economically disadvantaged status are shown in Panel (a) of Figure C.2. I find that charter openings decrease the fraction of economically disadvantaged students among switchers compared to schools located more than 5 miles away from the charter. On the contrary, there is a significant increase in the fraction of economically disadvantaged students among stayers. There is no significant impact on the newcomers. When it comes to the student composition in terms of student achievement level, as shown in Panel (b) and Panel (c), I find that charter openings significantly increase the average baseline Math and ELA scores of switchers compared with the switchers in TPS located more than 5 miles away from the charter. All the above evidence suggests that charter schools "cream-skim" students from TPSs. Students who leave TPSs after charter openings are more likely to be non-poor and high-achieving.

D Pre-Trend Test Results for School Competition Effects

The validity of using a DID model to estimate the causal impact of charter school openings depends on the assumption that TPSs located near new charters and those located farther away exhibit parallel trends in outcomes prior to the introduction of the charter schools. I examine the parallel trend assumption using the event study model specified in equation 3.

I plot the event study estimates to assess the pre-trends in teachers' grade change, and I find no evidence of a violation of parallel trends (results are shown in Figure C.6). Figure C.7 plots the trends in the differences in school quality and student characteristics between schools/teachers exposed to charter entry and those not exposed to charter entry. There is no significant evidence of the violation of parallel assumption in both ELA and Math classes.

E Estimation of School Choice and Competition Model

E.1 First-order condition of education production function

To solve for $\frac{\partial Proficiency_{jt}}{\partial Quality^{T}_{jt}}$, I first aggregate equation 5 to the school level, and the proficiency rate in school j in year t is specified below:

$$Proficiency_{jt} = \frac{\Omega + \overbrace{(\beta_l + \beta_{diff}) Quality_{jt}^T * N_{jt}^{stu_hach}}^{Aggregated\ Effects\ on\ HighAch\ Students} + \overbrace{\beta_l * (N_{jt}^{stu} * \lambda_{jt} - Quality_{jt}^T * N_{jt}^{stu_hach})}^{Aggregated\ Effects\ on\ LowAch\ Students}}{N_{jt}^{stu}}$$

where Ω represents the aggregated effects from student-, teacher-, school-level inputs that are unrelated to $Quality_{jt}^T$. $N_{jt}^{stu} * \lambda_{jt} - Quality_{jt}^T * N_{jt}^{stu_hach}$ represents the total number of low-achieving students assigned to high-quality teachers. β_l is the effect of high-quality teachers on low-achieving students' proficiency level and $\beta_l + \beta_{diff}$ is the effect of high-quality teachers on high-achieving students' proficiency level.

E.2 Supply Model Estimation

The probability density function of $\tilde{\omega}$ is:

$$f(\tilde{\omega} \mid \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} exp[-\frac{1}{2}(\frac{\tilde{\omega} - \mu}{\sigma})^2]$$

ω_{jt} and $\tilde{\omega}_{jt}$ can be calculated using the first order condition of the supply model:

$$\frac{\partial \pi_{jt}}{\partial Quality_{jt}^T} = \frac{\partial share_{jt}}{\partial Quality_{jt}^T} + \omega_{jt} \frac{\partial Proficiency_{jt}}{\partial Quality_{jt}^T}$$

Then

$$\frac{\partial \pi_{jt}}{\partial Quality_{jt}^T} = \begin{cases} \frac{\partial share_{jt}}{\partial Quality_{jt}^T} + \omega_{jt} \frac{\partial Proficiency_{jt}}{\partial Quality_{jt}^T} = 0, & if \quad \underline{Quality_{jt}^T} < Quality_{jt}^T < \overline{Quality_{jt}^T} \\ \frac{\partial share_{jt}}{\partial Quality_{jt}^T} + \omega_{jt} \frac{\partial Proficiency_{jt}}{\partial Quality_{jt}^T} < 0, & if \quad Quality_{jt}^T = \overline{Quality_{jt}^T} \\ \frac{\partial share_{jt}}{\partial Quality_{jt}^T} + \omega_{jt} \frac{\partial Proficiency_{jt}}{\partial Quality_{jt}^T} > 0, & if \quad Quality_{jt}^T = \underline{Quality_{jt}^T} \end{cases}$$

where $\frac{\partial share_{jt}}{\partial Quality_{jt}^T}$ can be recovered using the estimates in the demand function and $\frac{\partial Proficiency_{jt}}{\partial Quality_{jt}^T}$ can be recovered using the estimates in the education production function. When $Quality_{jt}^T > \overline{Quality_{jt}^T}$, I define the corresponding ω and $\tilde{\omega}$ as the upper thresholds, denoted by $\overline{\omega}$ and $\overline{\tilde{\omega}}$, respectively. When $Quality_{jt}^T < \underline{Quality_{jt}^T}$, I define the corresponding ω and $\tilde{\omega}$ as the lower thresholds, denoted by $\underline{\omega}$ and $\underline{\tilde{\omega}}$, respectively.

I estimate μ and σ using the maximum likelihood method, where parameter estimates

maximize the probability of observing $\tilde{\omega}$. The likelihood is

$$L(\mu,\sigma) = \begin{cases} \prod_{j,t} f(\tilde{\omega} \mid \mu,\sigma), & if \quad \underline{Quality_{jt}^T} < Quality_{jt}^T < \overline{Quality_{jt}^T} \\ \prod_{j,t} F(\overline{\tilde{\omega}} \mid \mu,\sigma), & if \quad Quality_{jt}^T = \overline{Quality_{jt}^T} \\ \prod_{j,t} (1 - F(\underline{\tilde{\omega}} \mid \mu,\sigma)), & if \quad Quality_{jt}^T = \underline{Quality_{jt}^T} \end{cases}$$

E.3 First Stage Results

Table B.9 presents the first-stage for the endogenous school characteristics. Teacher salary overall has positive impacts on school proficiency rates. A higher median income level in the neighborhood is associated with a lower proportion of poor students at school; schools located in the neighborhood with a higher fraction of white residents also have higher fractions of white students at school. Moreover, graduate-level enrollment in higher education institutions (distance weighted) is positively correlated with the fraction of high-achieving students assigned to high-quality teachers, and the strength of this correlation becomes higher if the school is located closer to institutes with teacher certification programs. In each regression, I report the statistics of F-test for the joint significance of all instrumental variables. All the F statistics are larger than 12, suggesting that weak instruments are not a concern.

F Supplementary Tables

Table B.1: Effects of charter openings on the enrollment in TPSs

	(1) Total Enrollment	(2) Enrollment in competition grades	(3) Enrollment in non-competition grades
		Panel A: 5 Mile Radius	
Treat*Post	-11.195***	-8.286**	.464
	(4.188)	(3.315)	(3.513)
N	119697	84430	14191
		Panel B: 5 Mile Radius, Exclude 5-10	
Treat*Post	-13.870***	-6.302*	-1.414
	(4.327)	(3.526)	(3.175)
N	99213	69274	12112
		Panel C: 10 Mile Radius	
Treat*Post	-11.068***	-3.742	-1.103
	(3.564)	(2.741)	(2.683)
N	103288	72627	12320

Notes: This table reports the estimated effect of charter school openings on the enrollment in TPSs. Column (1) shows the effect on the total enrollment, column (2) shows the effect on the enrollment in competition grades that both the TPS and the new charter school nearby serve, column (3) shows the effect on the enrollment in non-competition grades that the new charter school nearby does not serve. All regressions include school-by-cohort fixed effects, cohort-by-year fixed effects, and school-level linear time trend. Robust standard errors clustered at school level are reported in parenthesis; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.2: Effects on Characteristics of Teacher Leavers, Newcomers, and Stayers

	Leavers			Newcomers			Stayers		
	Education	Experience	Value-added	Education	Experience	Value-added	Education	Experience	Value-added
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Panel A: Math				
Treat*Post	.012	-.351	.095	-.083*	-.549	-.010	-.011	-.052	-.029
	(.054)	(.820)	(.126)	(.048)	(.732)	(.114)	(.012)	(.223)	(.027)
N	20827	20642	18625	19247	19195	17326	57834	57834	55831
					Panel B: ELA				
Treat*Post	-.066	-.304	.176	.019	.472	.066	.016	.098	-.032
	(.055)	(.750)	(.133)	(.056)	(.718)	(.106)	(.013)	(.222)	(.032)
N	19266	19136	17170	18089	18063	16195	54861	54861	49683

Notes: This table shows the estimated effects of charter openings on the characteristics of teacher leavers, newly hired teachers, and teacher stayers in TPSs, including the proportion of teachers with graduate degrees, average experience, and average value-added. The regressions use school-level data. Panel (A) presents the effects in Math and Panel (B) presents the effects in ELA. In each regression, I control for school quality (measured by the average lagged test scores in Math and ELA at the school level), school by cohort fixed effects, cohort by year fixed effects, and linear time trend at the school level. Each regression is weighted by the school enrollment size. Robust standard errors clustered at school level are reported in parenthesis; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.3: Effects of charter openings on the quality of TPSs

	Proficiency Rate		Average Test Scores	
	(1)	(2)	(3)	(4)
	ELA	Math	ELA	Math
Panel A: 5 Mile Radius				
Treat*Post	-.009***	.001	-.018***	-.014**
	(.003)	(.004)	(.006)	(.007)
Lagged scores ELA	.015	-.016	-.019	-.088
	(.023)	(.019)	(.082)	(.084)
Lagged scores Math	.069***	.086***	.199***	.228***
	(.011)	(.014)	(.054)	(.036)
N	81024	81024	81029	81029
Panel B: 5 Mile Radius, Exclude 5-10				
Treat*Post	-.011***	-.001	-.026***	-.021***
	(.003)	(.004)	(.006)	(.008)
Lagged scores ELA	.017	-.008	-.030	-.078
	(.022)	(.018)	(.089)	(.097)
Lagged scores Math	.066***	.073***	.203***	.203***
	(.013)	(.016)	(.062)	(.042)
N	65985	65985	65990	65990
Panel C: 10 Mile Radius				
Treat*Post	-.006***	.000	-.018***	-.016**
	(.002)	(.003)	(.005)	(.006)
Lagged scores ELA	.019	-.009	-.021	-.080
	(.022)	(.018)	(.086)	(.093)
Lagged scores Math	.066***	.078***	.202***	.212***
	(.012)	(.016)	(.060)	(.041)
N	68827	68827	68832	68832

Notes: This table reports the estimated effect of charter school openings on the proficiency rates and average test scores in TPSs. The regressions use school-level data. In each regression, I control for school quality (measured by the average lagged test scores in Math and ELA at the school level), school by cohort fixed effects, cohort by year fixed effects, and linear time trend at the school level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.4: Effects of charter openings on class structure in TPSs

	(1) Number of Classes	(2) Number of Teachers	(3) Class Size	(4) Number of Classes Per Teacher	(5) Student-Teacher Ratio
			Panel A: Math		
5 Mile Radius					
Treat*Post	-1.024***	-.468***	.310*	.099***	1.834***
	(.301)	(.145)	(.166)	(.026)	(.429)
Treat*Post*High Quality				.042	-.713
				(.048)	(.933)
Mean	14.622	8.768	18.980	1.873	35.035
N	64154	65447	65847	385169	387860
5 Mile Radius, Exclude 5-10					
Treat*Post	-1.104***	-.468***	.223	.137***	2.035***
	(.303)	(.138)	(.159)	(.026)	(.435)
10 Mile Radius					
Treat*Post	-.629***	-.301***	.164	.122***	1.052***
	(.227)	(.110)	(.139)	(.024)	(.364)
			Panel B: ELA		
5 Mile Radius					
Treat*Post	-1.174***	-.582***	.321*	.084***	1.528***
	(.337)	(.147)	(.187)	(.029)	(.434)
Treat*Post*High Quality				.036	-.790
				(.047)	(.908)
Mean	15.485	8.844	18.796	1.949	36.516
N	64593	63428	64670	375371	378513
5 Mile Radius, Exclude 5-10					
Treat*Post	-.905***	-.545***	.197	.116***	1.687***
	(.320)	(.141)	(.176)	(.030)	(.451)
10 Mile Radius					
Treat*Post	-.421	-.350***	.109	.116***	1.444***
	(.270)	(.120)	(.154)	(.027)	(.372)

Notes: This table shows the estimated effects of charter openings on multiple class structure outcomes in TPSs, including the number of classes offered, the number of teachers, the average class size, the number of classes per teacher, and the student-teacher ratio in both Math and ELA classes. Columns (1)-(3) use school-level data and I control for school quality (measured by the average lagged test scores in Math and ELA at the school level), school by cohort fixed effects, cohort by year fixed effects, and linear time trend at the school level. Columns (4)-(5) use teacher level data and I control for school quality, school composition measured by the lagged fraction of economically disadvantaged students, teacher quality measured by teaching experience (centered), education level (whether having a graduate degree), and teacher value-added, school by cohort fixed effects, grade fixed effects, and cohort by year fixed effects. Robust standard errors clustered at school level are reported in parenthesis; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.5: Effects of charter openings on class structure in TPSs: Triple DID

	Number of Students		Number of Classes	
	(1)	(2)	(3)	(4)
	ELA	Math	ELA	Math
Panel A: DID Model				
Treat*Post	1.528***	1.834***	.084***	.099***
	(.434)	(.429)	(.029)	(.026)
Panel B: Triple DID Model				
Treat*Post*Overlapped	1.687***	2.035***	.116***	.137***
	(.451)	(.435)	(.030)	(.026)
N	297354	305918	294815	303796

Notes: This table reports the estimated effects of charter school openings on the class structure in TPSs, measured by the number of students and classes assigned to each teacher. Panel A reports the estimates using the difference-in-difference model and Panel B reports the estimates using the triple difference-in-difference model. The regressions use teacher-level data and control for school quality measured by lagged average test scores in Math and ELA, school composition measured by the lagged fraction of economically disadvantaged students, and teacher quality measured by teaching experience (centered), education level (whether having a graduate degree), and teacher value-added. All regressions include school-by-cohort fixed effects, grade fixed effects, and cohort-by-year fixed effects. Robust standard errors clustered at school level are reported in parenthesis; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.6: Effects of charter openings on the allocation of teachers across grades

	(1) ELA	(2) Math
Panel A: 5 Mile Radius, Exclude 5-10		
Treat*Post	.005	-.003
	(.009)	(.009)
Treat*Post*High Quality	.010	.011
	(.020)	(.021)
N	203852	215224
Panel B: 10 Mile Radius		
Treat*Post	-.006	-.010
	(.008)	(.008)
Treat*Post*High Quality	-.007	-.001
	(.019)	(.019)
N	214277	226589

Notes: This table reports the estimated effect of charter school openings on whether TPSs reallocate teachers across grades. The outcome variable is the indicator of whether the teacher is in a different grade than the last year. The regressions use teacher-level data and control for school quality measured by lagged average test scores in Math and ELA, and teacher quality measured by teaching experience (centered), education level (whether having a graduate degree), and teacher value-added. All regressions include school-by-cohort fixed effects and cohort-by-year fixed effects. Robust standard errors clustered at school level are reported in parenthesis; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.7: Effects of charter openings on teacher-student allocation

	Math		ELA	
	Econ Disadvantaged %	Average Baseline Score	Econ Disadvantaged %	Average Baseline Score
	(1)	(2)	(3)	(4)
Panel A: 5 Mile Radius, Exclude 5-10				
Treat*Post	-.939**	.015	-.741*	-.001
	(.442)	(.010)	(.448)	(.009)
Treat*Post*High Quality	2.187**	-.112***	1.684*	-.091***
	(.899)	(.034)	(.893)	(.030)
N	221434	188556	224854	191287
Panel B: 10 Mile Radius				
Treat*Post	-.185	-.004	-.259	-.011
	(.369)	(.008)	(.378)	(.008)
Treat*Post*High Quality	1.504*	-.072**	2.272**	-.092***
	(.834)	(.031)	(.893)	(.028)
N	233362	198515	235824	200481

Notes: This table reports the estimated effects of charter school openings on the the characteristics of students assigned to different teachers in TPSs. The regressions use teacher-level data. Column (1) and Column (3) show the effects on the proportion of economically disadvantaged students among all students taught by each teacher; Column (2) and Column (4) show the effects on the average baseline scores in Math/ELA among all students taught by each teacher. The regressions control for school quality measured by lagged average test scores in Math and ELA, school composition measured by the lagged fraction of economically disadvantaged students, and teacher quality measured by years of teaching experience, education level (whether having a graduate degree), and teacher value-added. All regressions include school-by-cohort fixed effects, grade fixed effects, and cohort-by-year fixed effects. Robust standard errors clustered at school level are reported in parenthesis; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.8: Education Production Function Estimates: First Stage

	Poor%	White%
	(1)	(2)
Neighborhood White% Lagged	-.001***	.005***
	(.000)	(.000)
Neighborhood Median Income Lagged	-.000***	-.000***
	(.000)	(.000)
Student FE	YES	YES
N	1687271	1687271
F Statistics	13357	9349

Notes: This table shows the estimates in first stage of the instrumental variable regression of the education production function. Estimated coefficients on selected variables are reported. The regressions use student-level data and I control for student fixed effects. Standard errors are clustered at student level; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

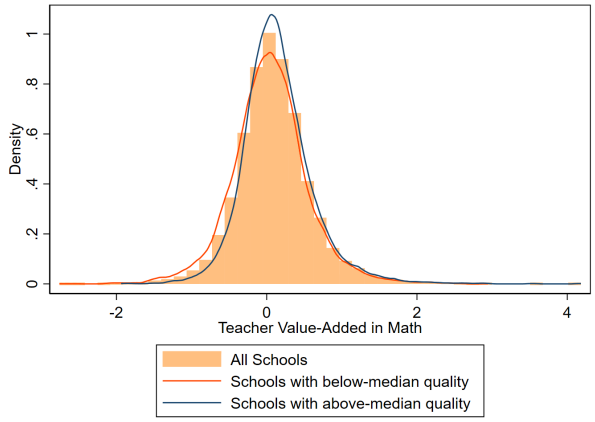
Table B.9: School Competition Model Estimates: First Stage

	Proficiency Rate	Poor%	White%	High-achieving students assigned to high-quality teachers%
	(1)	(2)	(3)	(4)
Teacher Salary (in thousands)				
Experience(0-4),MA	.239***	-.110***	-.018***	.037**
	(.012)	(.006)	(.003)	(.015)
Experience(5-9),MA	.208***	-.105***	-.020***	.023*
	(.010)	(.005)	(.002)	(.013)
Experience(10-14),MA	.183***	-.089***	-.021***	.013
	(.010)	(.005)	(.002)	(.013)
Experience(15+),MA	.204***	-.061***	-.013***	.006
	(.008)	(.004)	(.002)	(.010)
Experience(0-4),BA	.293***	-.116***	-.023***	-.029*
	(.012)	(.006)	(.003)	(.016)
Experience(5-9),BA	.282***	-.094***	-.018***	-.019
	(.011)	(.006)	(.003)	(.014)
Experience(10-14),BA	.270***	-.085***	-.015***	-.013
	(.010)	(.005)	(.002)	(.013)
Experience(15+),BA	.224***	-.076***	-.012***	-.014
	(.008)	(.004)	(.002)	(.011)
Neighborhood Demographics				
Neighborhood White% Lagged	.012***	.002***	.003***	-.001*
	(.001)	(.000)	(.000)	(.001)
Neighborhood Median Income Lagged	-5.868***	-1.052***	-1.814***	3.302***
(in millions)	(.651)	(.346)	(.158)	(.832)
College Enrollment at Graduate Level				
Enrollment at graduate level 2-year lagged	-.035***	.013***	.005***	.006
	(.005)	(.003)	(.001)	(.007)
Enrollment at graduate level * Mean distance	.000***	-.000***	-.000**	-.000
to colleges with teacher certification programs	(.000)	(.000)	(.000)	(.000)
School FE	YES	YES	YES	YES
N	10807	10807	10807	10807
F	122.156	42.505	41.607	12.135

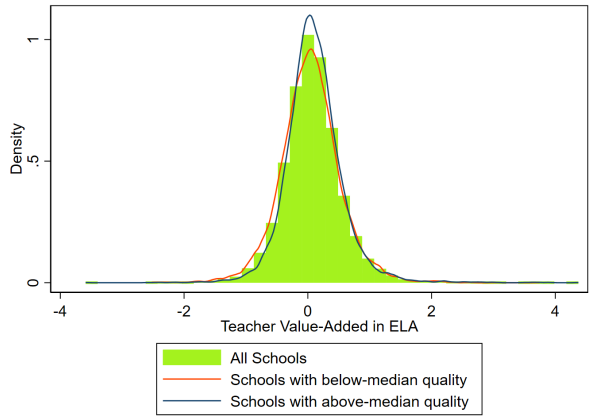
Notes: This table shows the estimates in first stage of the instrumental variable regression in the school demand model estimation. I regress all the endogenous variables in the student demand model on the three sets of instrumental variables. The regressions use school-level data and I control for school fixed effects. Standard errors are clustered at school level; *** p<0.01, ** p<0.05, * p<0.1

G Supplementary Figures

Figure C.1: The distribution of teacher value-added by school quality



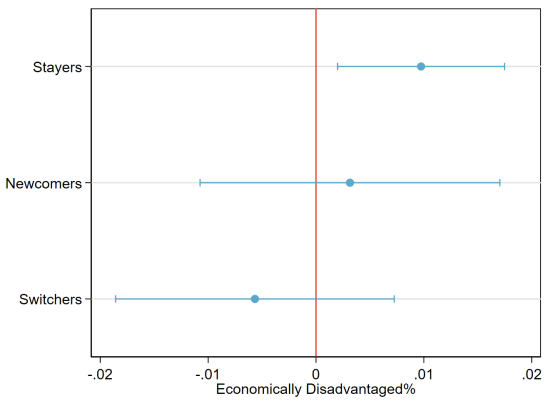
(a) Math



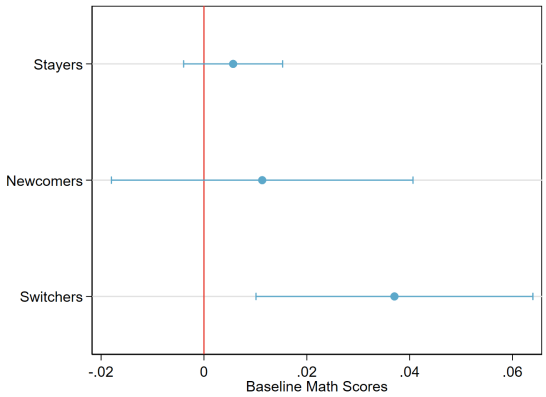
(b) ELA

Notes: This figure shows the distribution of teacher value-added in Math and ELA across all schools and by school quality level. I categorize schools based on whether the school's average test score in Math/ELA in the prior year is larger than the state median test score or not. I conduct a statistical t-test to compare the means of teacher value-added between schools with above-median quality and schools with below-median quality and find the mean of teacher value-added in schools with above-median quality is statistically higher than that in schools with below-median quality at 1% significance level. The difference in teacher value-added between above-median quality and below-median quality schools is 0.103 in Math and 0.061 in ELA, t statistics for the difference in mean are 12.89 and 7.79 with the p values of 0.000. I also conduct a two-sample Kolmogorov-Smirnov Test to examine the difference in the distribution of teacher value-added between the two groups of schools and it suggests that the two distributions are statistically significantly different at 1% significance level in both Math and ELA. The approximate asymptotic p-values for the combined Kolmogorov-Smirnov Test are 0.000 in Math and ELA.

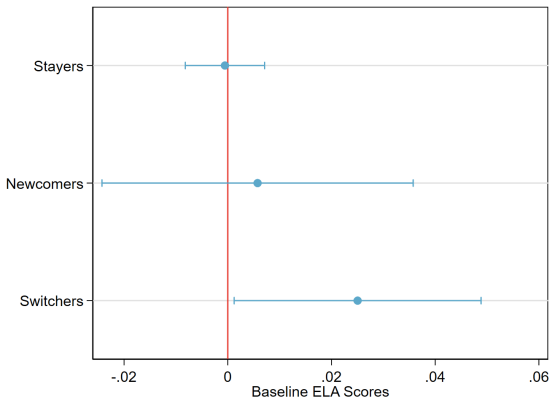
Figure C.2: Effects of charter openings on stayers, newcomers, and switchers in TPSs



(a) Economically Disadvantaged%



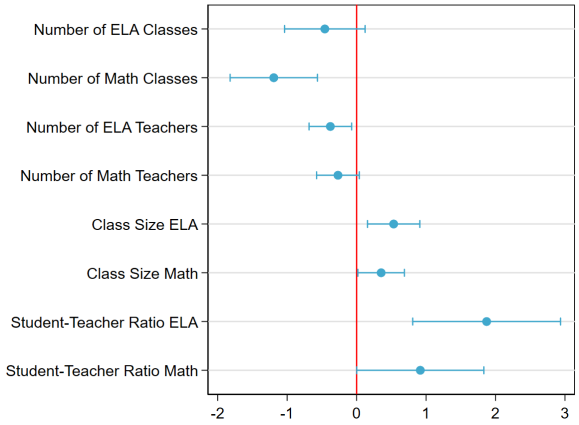
(b) Baseline Math Scores



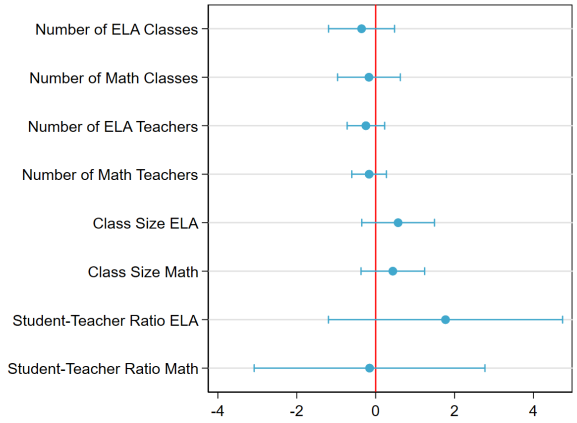
(c) Baseline ELA Scores

Notes: This figure shows the estimated effects of charter openings on student body composition in TPSs, separately for stayers, newcomers, and switchers in TPSs. In each regression, I control for school quality (measured by the average lagged test scores in Math and ELA at the school level), school by cohort fixed effects, cohort by year fixed effects, and linear time trend at the school level. Each regression is weighted by the school enrollment size. I plot the point estimate and the 95% confidence intervals for each regression. Standard errors are clustered at the school level.

Figure C.3: The effects of charter openings on class structure by overlapped and non-overlapped grades



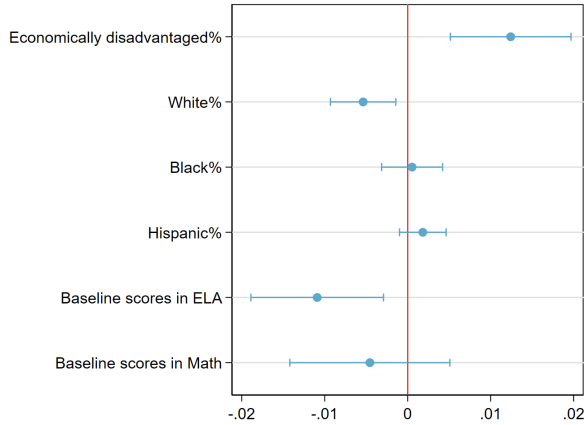
(a) Overlapped Grades



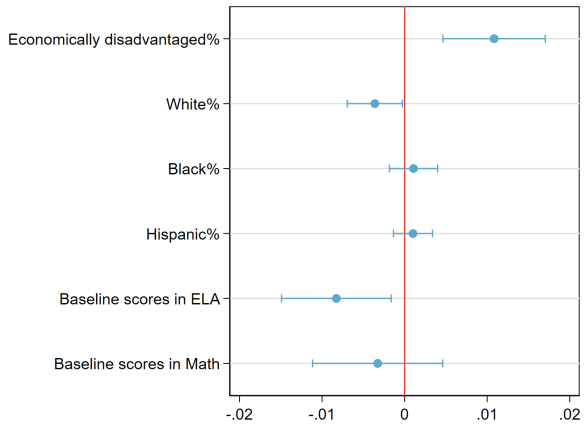
(b) Non-overlapped Grades

Notes: This figure shows the estimated effects of charter openings on multiple class structure outcomes in TPSs, including the number of classes offered, the number of teachers, the average class size, and the student-teacher ratio in both Math and ELA classes. I separately plot the estimates in overlapped grades that both the TPS and the new charter school serve, and in non-overlapped grades. In each regression, I control for school quality (measured by the average lagged test scores in Math and ELA at the school level), school by cohort fixed effects, cohort by year fixed effects, and linear time trend at the school level. Each regression is weighted by the school enrollment size. I plot the point estimate and the 95% confidence intervals for each regression. Standard errors are clustered at the school level.

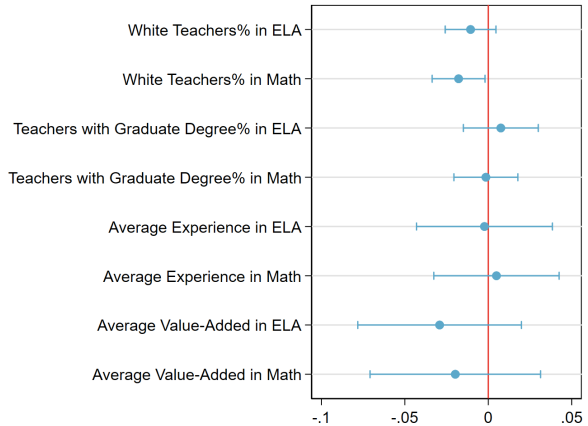
Figure C.4: The effects of charter openings on student and teacher body composition in TPSs: Robustness



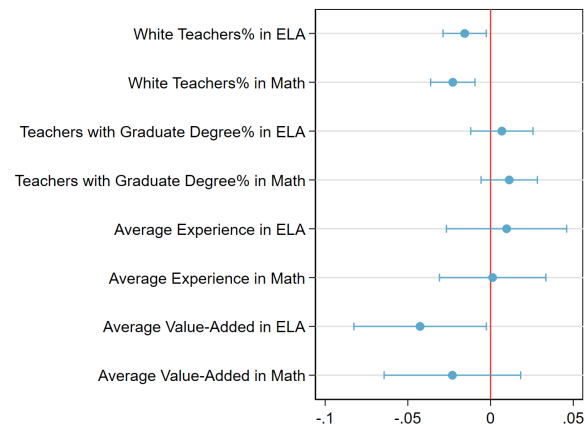
(a) Student Composition, 5 Mile Radius,Exclude 5-10



(b) Student Composition, 10 Mile Radius



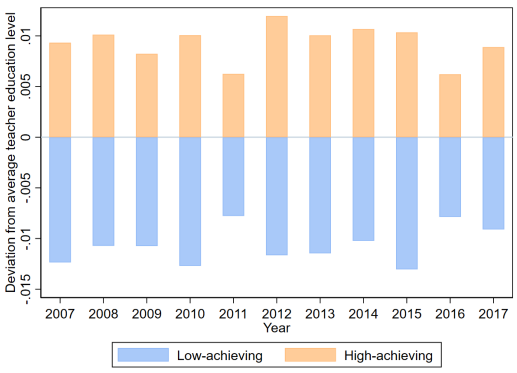
(c) Teacher Composition, 5 Mile Radius, Exclude 5-10



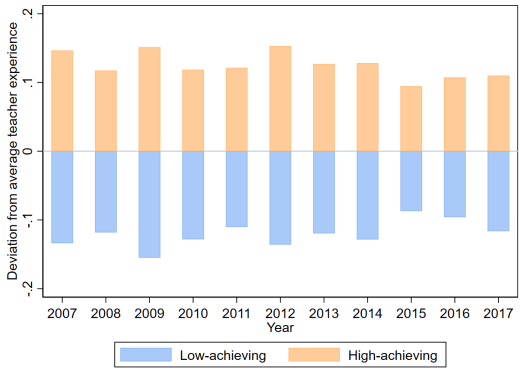
(d) Teacher Composition, 10 Mile Radius

Notes: This figure shows the estimated effects of charter openings on student and teacher body composition in TPSs, including the proportion of economically disadvantaged students, white students, black students, hispanic students, and the average Math and ELA baseline scores of students who are left in TPSs, the proportion of white teachers, the proportion of teachers with graduate degrees, the average teaching experience, and the average value-added in Math and ELA. The unit of the teaching experience is decade in this figure. In each regression, I control for school quality (measured by the average lagged test scores in Math and ELA at the school level), school by cohort fixed effects, cohort by year fixed effects, and linear time trend at the school level. Each regression is weighted by the school enrollment size. I plot the point estimate and the 95% confidence intervals for each regression. Standard errors are clustered at the school level.

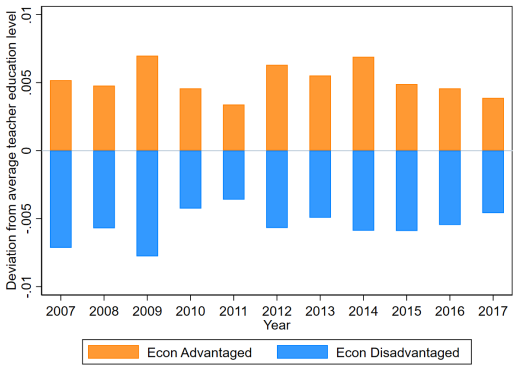
Figure C.5: Gaps in teacher quality within TPSs by achievement level and economically disadvantaged status



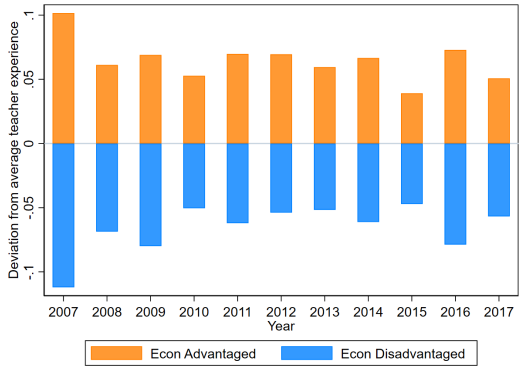
(a) Teacher Education Level



(b) Teacher Experience



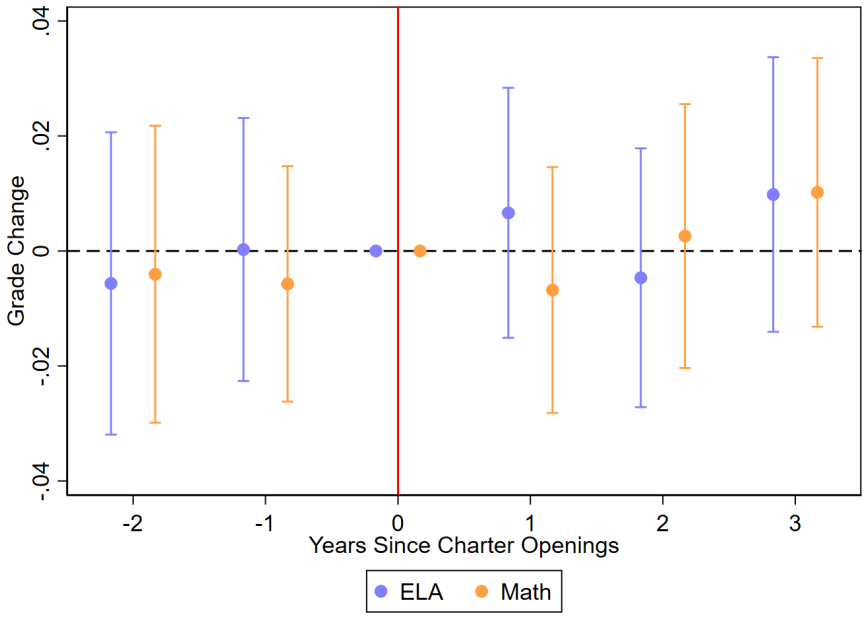
(c) Teacher Education Level



(d) Teacher Experience

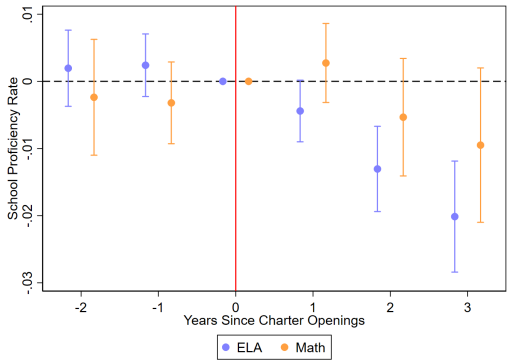
Notes: These two figures plot the deviations in teacher quality obtained by different students from the average teacher quality in the same school-grade cell.

Figure C.6: Pretrend tests for the analysis of how charter openings affect the allocation of teachers across grades in TPSs

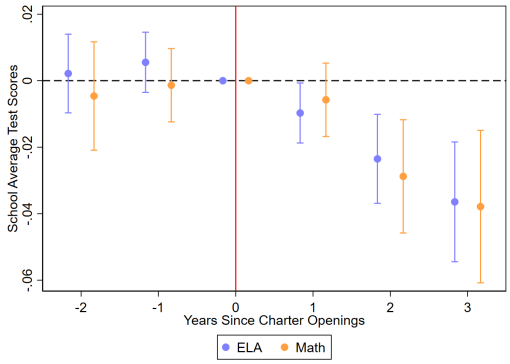


Notes: This figure plots the estimated effects of charter openings on the probability of being moved to a different grade in TPSs, using the event study model specified in equation 3 . The outcome variable is the indicator of whether the teacher is in a different grade than the last year. The regression uses teacher-level data and control for school quality measured by lagged average test scores in Math and ELA, and teacher quality measured by teaching experience, education level (whether having a graduate degree), and teacher value-added. All regressions include school-by-cohort fixed effects and cohort-by-year fixed effects. I plot the point estimate and the 95% confidence intervals. Standard errors are clustered at the school level.

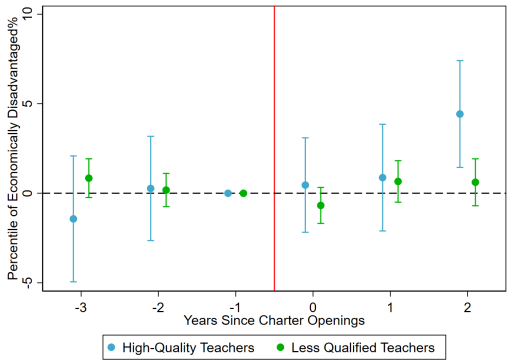
Figure C.7: Pretrend tests for how charter openings affect school quality and teacher-student allocation



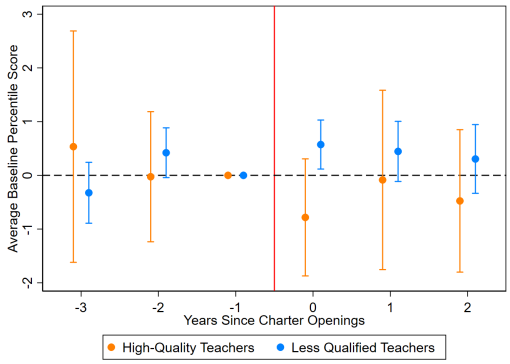
(a) School Proficiency Rate



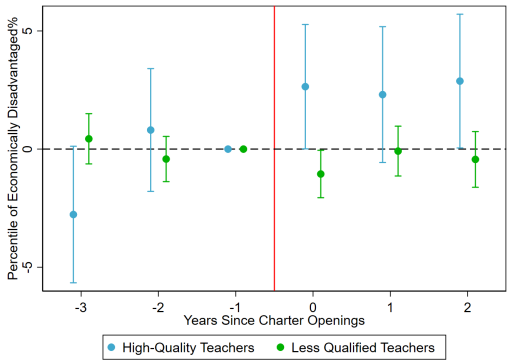
(b) School Average Test Scores



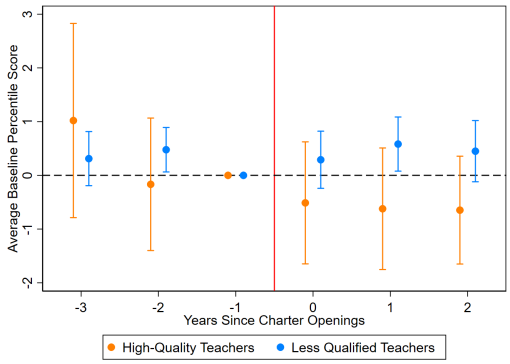
(c) MATH:Percentile of Econ Disadvantaged%



(d) MATH:Average Baseline Percentile Score



(e) ELA:Percentile of Econ Disadvantaged%



(f) ELA:Average Baseline Percentile Score

Notes: This figure plots the estimated effects of charter openings on school quality and teacher-student allocation in TPSs, using the event study model specified in equation 3. The school quality pretrend tests use school-level data and the teacher-student allocation pretrend tests use teacher-level data. I control for school quality measured by lagged average test scores in Math and ELA, and teacher-student allocation pretrend tests also control for teacher quality measured by teaching experience, education level (whether having a graduate degree), and teacher value-added, school composition measured by the lagged fraction of economically disadvantaged students,. All regressions include school-by-cohort fixed effects and cohort-by-year fixed effects. Teacher-student allocation pretrend tests also control for grade fixed effects. I plot the point estimate and the 95% confidence intervals. Standard errors are clustered at the school level.