Competition and School Quality: Evidence from Centralized Assignment*

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Abstract

Using competition to increase school quality is a key rationale for promoting choice within school districts, but evidence on this channel has generally been indirect. In this project, I directly estimate a theoretically motivated measure of schools' competitive pressures using centralized assignment data from a large urban school district's deferred-acceptance mechanism. I find that competitive pressure within the district is dispersed, and most of the variation in competition is unexplained by concentration. While there is substantial pressure to attract more students to some schools, these competitive incentives do not induce schools to raise their school effectiveness on academic achievement. Instead, schools respond by shifting discretionary expenditures from administration to instruction.

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1 Introduction

There has been a surge in market-based reforms to U.S. public school districts over the past two decades. While proposals like school vouchers or charter schools expansions are generally mired in controversy, many large public school districts across the U.S. have introduced sophisticated mechanisms that facilitate school choice within the existing portfolio of schools in the district.[1] These mechanisms are appealing to policymakers since they are an inexpensive way to increase competition between schools and boost student achievement. However, skeptics argue that competition between public schools is inherently limited due to capacity constraints, residential segregation, and informational frictions.

Existing evidence on the effects of competition on school quality is mixed in the public-school context. For example, Hoxby (2000) and Card et al. (2010) show that increasing the number of school districts in an area causally raises the area's average test scores, but it's not clear whether the effects are driven by school responses to competition or other channels like student sorting.[2] Recent papers using student-level data show that families do not appear to choose schools based on school effectiveness (for example, Abdulkadiroglu et al., 2017b; Walters, 2018), casting doubt on the competitive incentives for raising school effectiveness.

This project revisits the magnitude and effects of competition in public schools to provide two contributions — a direct estimate of the competitive pressure that schools face due to intradistrict school choice and novel evidence on the relationship between competition and school effectiveness. I show that competitive pressure in my sample is generally low, but can be substantial at some schools, including ones in the traditional sector. The competitive pressure is negatively correlated with conventional measures of concentration, but the majority of the variation in competitive pressure is unexplained by concentration. I find that competition alone does not lead to increases in school effectiveness, but it does induce schools to devote discretionary spending towards instruction rather than administration.

The setting of the project is a large urban school district in the U.S. between 2009 and 2017. This setting offers several key advantages for measuring the level and effects of competition between public schools. First, the district has a large and diverse range of school options, and they give individual schools unusually high autonomy in determining the personnel and course offerings at the school. Second, the district introduced a centralized student assignment mechanism during my sample period; the mechanism generates detailed data on student preferences that allow me to directly quantify competition in the district. Third, I observe student-level panels in test scores as well as school-level expenditures, which allow me to characterize school inputs and outputs at an unusually high level of detail. Finally, I can leverage the introduction of coordinated choice as a source of external variation in the competitive environment to test for the effects of competition on school outcomes.

I begin with a standard model to show that schools' competitive enrollment incentives can be summarized by one conceptual measure: the change in school enrollment in response to a change in its quality. Like past literature that modeled public school competition, I assume that schools choose a level of quality to balance the tradeoff between enrollment and the cost of quality provision.

[1] Whitehurst (2017) estimates that the share of large school districts in the U.S. that allow school choice nearly doubled from 29% in 2000 to 56% in 2016.

[2] A large literature in IO has emphasized that a higher concentration of firms does not necessarily imply less competition between firms (Bresnahan, 1989).

However, I deviate from past work by allowing for capacity constraints to bind, which is relevant for many schools in my setting. The model formalizes a simple intuition for when competition matters — schools face higher incentives to provide quality on the margin when quality improvements yield a greater relative increase in student enrollment.

A key focus of the project is to explicitly estimate the level of competitive pressure that schools face, so I show how the conceptual measure of competitive pressure can be mapped to empirical objects in my setting. A full empirical model of the market requires estimates of student demand, school capacities, and the market assignment mechanism. To quantify student demand for schools, I estimate an exploded logit discrete choice model using students' submitted rank order lists while allowing for rich interactions between observable student characteristics and school characteristics. Meanwhile, I directly observe proxies for schools' capacities and the assignment mechanism used to determine student offers. The resulting empirical model appears to capture the main elements of the assignment system, closely replicating observed patterns in rank choices and outcomes for a holdout sample of students.

I find that the estimated competitive incentives for enrollment within the district are generally low, but can be substantial at some schools. Capacity constraints bind at 32% of the schools in the district. The median school expects enrollment to increase by 8.3% in response to an improvement equivalent to the utility value of reducing the commuting distance by 1km. Traditional schools and high schools tend to face the lowest degrees of competition, while elementary schools and alternative model schools (like magnet and charter schools) generally face substantial competitive incentives at the margin. Competitive pressure is lower, on average, in schools facing high market concentration, but over 95% of the variation in competitive pressure remains after conditioning on concentration.

With the estimates of competitive pressure in hand, I then use two complementary sources of variation to test for the effects of competition on school outcomes. I draw similar conclusions from each approach. The first empirical strategy exploits cross-sectional variation in competitive pressure across schools. The second empirical strategy studies within-school changes following the introduction of centralized assignment. The conclusions from the two empirical strategies are remarkably similar despite the different sources of variation used in the two approaches. Schools appear to respond to competition by shifting expenditures from administration to instruction but not by increasing school value-added on test scores.

In the first approach, I compare observably similar schools that face different degrees of competitive pressure and find little difference in their school effectivenesses but large differences in their discretionary expenditures. I estimate a reasonably precise and approximately zero correlation between competitive pressure and a school's value-added on state standardized exams. The value-added measures are estimated from student-level panel data and control for the differences in student composition by construction (Chetty et al., 2014). As a result, it is unsurprising that the relationship between competition and value-added does not change meaningfully after adding controls for student composition. On the other hand, I find that schools facing high competitive pressures devote a greater share of their budgets towards instructional purposes. These estimates are also robust to controls for student composition and school type, bolstering the interpretation that the results reflect the effects of competition as opposed to other channels.

To address any remaining concerns that cross-sectional estimates are confounded by unobserved differences between schools, I compare changes in school outcomes following the introduction of the centralized assignment mechanism for schools facing different levels of competitive pressure. This differences-in-differences strategy allows me to control flexibly for omitted variables by including school fixed effects and flexible time trends by school type. My results mirror the conclusions from the cross sectional analysis. Although the assignment mechanism drastically lowered the costs of applying to different schools within the district, the greater degree of choice did not differentially increase value-added at competitive schools (relative to uncompetitive schools) over the five years after the introduction of centralized assignment. On the other hand, competitive schools were more likely to increase instructional spending following the introduction of the assignment mechanism. Moreover, both sets of results are robust to controlling for changes in student composition and do not appear to be driven by subsequent policy changes.

This paper contributes to the large literature on the downstream effects of school competition. Economists have long emphasized competition as a potentially important channel for inducing school-level improvements (Friedman, 1962; Hoxby, 2003). But empirical evidence on this channel has generally been indirect. Existing research often focuses on the effects of changes in the menu of schooling choices on school outcomes. In the school voucher context, examples include Hsieh and Urquiola (2006); Figlio and Hart (2014); Muralidharan and Sundararaman (2015), as well as the survey in Epple et al. (2017). In the charter school context, examples include Ridley and Terrier (2018); Gilraine et al. (2021). Studies using more general, market-level variation in district boundaries include Hoxby (2000); Rothstein (2007); Card et al. (2010). These studies tend to find mixed to positive effects of increasing choice on school outcomes, but as Urquiola (2016) points out, it is difficult to disentangle the competition channel from other spillover effects without explicitly modeling the competitive framework.

A more recent literature has taken a more IO approach to specify the market structure for schools and identify the competition channel. Neilson (2021) and Allende (2019) develop full equilibrium models of competition between private schools in Chile and Peru to determine schools' pricing and quality provision decisions. Bayer and McMillan (2005) model competition between public elementary schools in the San Francisco Bay Area to derive a theoretically motivated competition measure and assess its relationship to supply-side characteristics. Campos and Kearns (2022) estimate demand for schools using rank-order-preference data from the centralized assignment mechanism at the Los Angeles Unified School District. They show that introducing school choice at the neighborhood level increased school effectiveness, especially at schools facing more intense competition. My paper is closest to Campos and Kearns (2022) in the setting and approach, although I differ by explicitly considering enrollment-based fiscal concerns and potentially binding capacity constraints in determining competitive incentives. I also study a broader, market-level adoption in centralized choice rather than the more localized rollout in Campos and Kearns (2022), which may explain in part the differences in our findings.

The paper also relates to the literature on estimating student preferences over schools. Recent papers highlight that student demand for school effectiveness appears to be low, which would limit the potential for school choice to improve student outcomes (Hastings et al., 2008; Abdulkadiroglu et al., 2017b; Walters, 2018). However, without variation in school quality, it is difficult to infer whether the observed lack of responsiveness to school effectiveness is due to true preferences over school effectiveness or unobserved factors that are correlated with school effectiveness. My paper complements these results by providing an alternative supply-side test — if students value school effectiveness, then we should expect to see schools provide more school effectiveness when there is greater competitive pressure to do so. I also provide a methodological contribution to the growing literature on flexibly estimating models of student demand from centralized school assignment data (Hastings et al., 2008; Abdulkadiroglu et al., 2017a; Agarwal and Somaini, 2019). I show that by adding information on school capacities and the assignment algorithm, it is also straightforward to use the demand estimates to characterize the school-side enrollment incentives.[3]

The rest of the paper proceeds as follows. Section 2 first describes the school district and the student- and school-level data in more detail. Section 3 starts by specifying a simple model where schools compete for student enrollment and derives the key statistic capturing competitive pressure. Section 4 then describes how I empirically implement the model using data from the district. Section 5 presents estimates of competitive pressure using the empirical model of the market. Section 6 assesses the relationship between competitive pressure and school effectiveness. Finally, Section 7 concludes.

2 Setting and data

The setting of the project is a large urban school district in the U.S. The district's size and a high degree of school-level autonomy make it particularly suitable for studying competition between schools. Focusing on a single district allows me to observe detailed data on student preferences, academic performance, and school budgets, including from before the introduction of the centralized assignment system. This level of granularity is crucial for quantifying competition and its effects.

Like most other large urban school districts in the U.S., the district primarily enrolls lower-income, minority students. Table 1 presents summary statistics on the characteristics of students and schools in the district over the entire sample period (in the first column) as well as during the introduction of centralized assignment (in the second column). 71% of the students in the district qualify for either free or reduced lunch based on their family incomes. The district is majority-minority — 57% of students in the district are Hispanic, and 14% of students are black. Approximately 23% of students in the district are English language learners.

The district has drawn distinction for implementing a balanced approach to school choice that emphasizes school autonomy and experimentation within the district. In addition to traditional and magnet schools, which constitute approximately half of the schools in the district, the district also contains a growing number of charter schools and "innovation schools" that have additional autonomy over programming, budget, and staffing decisions. Even in the traditional sector, school administrators have direct authority in determining the size and composition of their staff, and most funding is allocated to schools on a per-student basis.

In Fall 2011, the district introduced a centralized assignment mechanism to match students to schools. Previously, the process through which students applied to non-neighborhood schools was uncoordinated and often undocumented. Centralizing admissions not only made the choice process transparent to all students, but the process also required students to actively participate in the

[3] More broadly, by characterizing school-side incentives as reflecting enrollment-based fiscal motives, the paper relates to the literature on soft budget constraints and the financial incentives facing non-profit and government owned institutions (Duggan, 2000; Glaeser and Shleifer, 2001; Kornai et al., 2003; Dafny, 2005). By consider potential responses in school characteristics rather than prices, the paper also relates to the growing IO literature on endogenous product attributes (Fan, 2013; Sweeting, 2013; Guajardo et al., 2016; Prince and Simon, 2017; Ito and Sallee, 2018).

choice mechanism and rank any schools they would prefer to their neighborhood schools. Student rankings are then combined with school-side priorities and a random tiebreaking lottery number through the student-proposing deferred acceptance algorithm, which matches each student to their most preferred stable match (Gale and Shapley, 1962).

I bring together several datasets for this project. The student-level data are provided by the school district from their administrative records and contain longitudinal unique identifiers that can be linked across datasets. The data cover the universe of students in the district, including those attending charter schools, but do not include students at private schools or in other districts. The data also vary in the time periods they cover due to changes in the data storage practices in the district.[4] I observe students' ranked choices and offers from the centralized assignment mechanism from the introduction of the system in 2012 to 2017. I also observe students' enrollment and demographic information from 2010 to 2017, and students' test scores on state exams from 2009 to 2017. Finally, I digitize school-level expenditures data between 2012 and 2014 from published budget books and match them to the administrative data. However, schools from the charter sector are not required to report their budgets in the budget books, so I do not observe expenditures from that sector.

3 Model of school competition

To fix ideas, I specify a simple model where schools attract students by making costly improvements to their quality. In this model, each school's competitive incentives can be summarized by a conceptual measure — the change in enrollment in response to a change in its quality. My model is based on the model in Card et al. (2010), but I extend the model to better reflect the considerations for schools in my setting. First, I explicitly model the school's objective as maximizing revenues from enrollments subject to the monetary costs of quality provision (as opposed to a general taste for market share subject to a non-monetary managerial effort cost). Second, I allow for potentially binding capacity constraints at the school level that dampen incentives for further improvement.

Assume that a student of type $\theta_i \sim F(\theta)$ has utility for attending school j with

$$u_{ij} = V_j + \beta(\theta_i) M_j - d_{ij} + \epsilon_{ij}, \tag{1}$$

where V_j is a common school quality term, M_j are fixed school characteristics whose value to students may depend on student type θ_i, d_{ij} is the commuting cost for student i to school j, and ϵ_{ij} is an idiosyncratic preference for school j. So, students trade off their taste for the school's observable and unobservable characteristics against the (distance) cost of attending. Since I focus on public schools within the same district, I assume that the primary cost for attendance is the commuting cost d_{ij}, which is normalized to 1 to serve as a numeraire.

Meanwhile, a school's objective is to maximize its revenues, so it solves

[4] The academic school year spans from the fall of a calendar year to the spring of the subsequent year. To avoid confusion, I refer to all academic years by their ending year (so I refer to SY2011-12 as 2012).

$$
\begin{aligned}
\max_{V_j} \ & Rn_j\left(V_j, V_{-j}\right) - c\left(V_j\right) n_j\left(V_j, V_{-j}\right) \\
\text{s.t. } & n_j\left(V_j, V_{-j}\right) \leq N_j \\
& Rn_j\left(V_j, V_{-j}\right) - c\left(V_j\right) n_j\left(V_j, V_{-j}\right) - C_j \geq 0,
\end{aligned} \tag{2}
$$

where R is the per-student revenue, $n_j\left(V_j, V_{-j}\right)$ is the total number of students who would enroll at school j given quality V_j at school j and quality V_{-j} at all other schools, and $c\left(V_j\right)$ is a strictly increasing function that captures the marginal cost of providing quality V_j to each student.[5] Two constraints enter the school's optimization problem. The first is a capacity constract, where the total enrollment of students at school j must be below the school's capacity N_j. The second constraint is a solvency constraint, which assumes that schools must collect enough revenue to meet their fixed costs (C_j). By modeling the quality choice as V_j, the common component of utility that are equally valued by all students, I abstract from more complex considerations where schools may adjust their optimal quality choice based on the selection of students in their market (as in McMillan, 2004).

The equilibrium enrollments $\{n_j\}$ are determined by student preferences, schools' quality choices, and the assignment mechanism. Under the assumptions laid out in the model, in any equilibrium where schools simultaneously choose their quality, a solvent school that is below the capacity constraint will satisfy the first order condition

$$
\left[R - c\left(V_j\right)\right] \left(\underbrace{\frac{\partial n_j\left(V_j, V_{-j}\right) / \partial V_j}{n_j\left(V_j, V_{-j}\right)}}_{= \partial \log n_j\left(V_j, V_{-j}\right) / \partial V_j} \right) = c'\left(V_j\right). \tag{3}
$$

$\left[R - c\left(V_j\right)\right] > 0$ and is strictly decreasing for a solvent school, and $c'\left(V_j\right)$ is strictly increasing. It follows that schools whose relative enrollment is more responsive to quality increases (V_j) will choose higher quality in equilibrium. In other words, holding all else equal, a school's competitive pressure for enrollment is summarized by its semi-elasticity of enrollment with respect to quality $\left(e_j \equiv \partial \log n_j\left(V_j, V_{-j}\right) / \partial V_j\right)$, and schools with a higher e_j will choose a higher quality in equilibrium.

On the other hand, when capacity constraints bind, schools do not have enrollment-based incentives to further increase school quality. Instead, the optimal school quality is determined by

$$
V_j^c = \min\left\{v_j : n_j\left(v_j, V_{-j}\right) \geq N_j\right\}. \tag{4}
$$

This expression formalizes a common critique that the expected effects of competition may be low if school capacities are binding. Furthermore, the expression implies that capacity-constrained schools may even choose to *decrease* school quality in response to competition-enhancing policies if the increase in the semi-elasticity of enrollment is accompanied by an increase in the *level* of enrollment.

Although the setup is stylized, it is sufficiently flexible to also formalize an alternate theory of school quality provision. This "non-strategic" theory is that schools simply provide the highest level of quality that they are able to afford, so the realized school quality $\tilde{V}_j$ satisfies

$$
\left[R - c\left(\tilde{V}_j\right)\right] n_j\left(\tilde{V}_j, V_{-j}\right) = C_j. \tag{5}
$$

[5]For simplicity, I've suppressed the dependence of n_j on fixed school characteristics and the distribution of student types.

This model can capture a common concern with the introduction of school choice, which is that the introduction of competing schools may lower enrollment at incumbent schools. This lower enrollment in turn requires the school to devote a greater share of expenditures towards covering fixed costs, ultimately eroding the quality of instruction. This alternate model centers on the level of enrollment and generates no *a priori* relationship between school quality and the semi-elasticity of enrollment with respect to quality (e_j).

4 Empirical model of the market

Given the richness of data available, it is straightforward to map the conceptual model from Section 3 to its empirical analogs. To ensure that my demand estimates are not confounded by subsequent changes that schools may have made following the centralized assignment mechanism, I focus on modeling the market from the first year of the match, which took place from Fall 2011 to Spring 2012. I focus on the market for entry grades at each school (0th grade for elementary schools, 6th grade for middle schools, and 9th grade for high schools) since mechanism take-up is highest for those grades and the interpretation of the choice process is the most straightforward. The model has three components: student demand, school supply, and the assignment mechanism. I discuss the empirical implementation of each component in turn.

4.1 Demand estimation

The school district uses student-proposing deferred acceptance as its assignment mechanism. When rank-order lists are unrestricted in length, the algorithm is strategy-proof, so it is optimal for students to truthfully report their preferences over schools to the assignment mechanism (Roth, 1982). The students' reported rank-order lists can then be directly interpreted as ranked preference data, which are key for estimating flexible models of discrete choice that allow for rich heterogeneity in preferences (Berry et al., 2004). Although the district limits the number of schools that students can rank to five, Figure A.1 shows that most students rank fewer than five schools. I take truth-telling as a reasonable approximation of student behavior and treat students' submitted rank order lists as a partial preference ordering over the set of all schools. Since students are guaranteed an offer at their neighborhood school, I assume that all unranked schools are less preferred than the student's neighborhood school.

In principle, the student demand Equation 1 is non-parametrically identified from variation in commuting distances d_{ij} and student rank order lists (Agarwal and Somaini, 2019). In practice, the distribution of student preferences is a high dimensional object, and I face a tradeoff between analytical tractability and the flexibility to capture realistic substitution patterns. Based on the results from Pathak and Shi (2018), where a richly specified multinomial logit model performed as well, and occasionally better, than a more computationally intensive mixed multinomial logit model in predicting student choices following a policy change, I use a flexible multinomial logit model as my baseline approach for approximating student demand.

I model the utility of school j for student i as

$$u_{ij} = \beta\left(X_i\right) X_j + \gamma\left(X_i\right) M_{ij} + V_j + \varepsilon_{ij}, \tag{6}$$

where I allow for preferences for school-specific characteristics X_j and student-school characteristics M_{ij} to differ by student characteristics X_i. Specifically, I allow for the student's utility to depend on a school's average student achievement (differentially by a student's gifted status and income), the share of minority and ELL students (differentially by a student's race and ELL status, respectively), and the distance between the student and the school (differentially by a student's race and income). I also include dummies for whether a student has a sibling currently enrolled at the school, and whether the school is the student's neighborhood school. V_j captures all of the components of the school's utility that are common to all students. Finally, ε_{ij} is distributed independently and identically from a type I extreme-value distribution.

I estimate the empirical demand Equation 6 from students' submitted rank order lists by exploded logit (Hausman and Ruud, 1987). I estimate the model separately for the elementary, middle, and high school entry grades, allowing the parameters to vary flexibly by grade. The model estimates are reported in Table 2. The parameters are generally precisely estimated and intuitive in sign and magnitude. Students are likely to rank schools that are their neighborhood schools and especially more likely to rank schools where they currently have a sibling, and they are less likely to rank schools that are far away. Hispanic and low income students find distance more costly, while black students find distance less costly. Furthermore, consistent with Goodreau et al. (2009); Idoux (2022), I find that black, Hispanic, and ELL students are relatively more likely to rank schools that have a higher share of similar students. Finally, I find that gifted students are relatively more likely to rank schools with high average achievement, whereas low income students are relatively less likely to do so. The estimates are also generally stable across specifications — when I vary the match-specific terms in the demand equation, the coefficients on the residential school, distance, and sibling controls remain quantitatively and qualitatively similar across specifications.

The primary concern with the multinomial logit model is that its independence of irrelevant alternatives (IIA) property would be a poor approximation of realistic substitution patterns. To assess whether the rich heterogeneity in Equation 6 alleviates the IIA concern, I directly assess the model's ability to fit substitution patterns by comparing the empirical choice shares for students' Top 2 choices to the predicted shares under Equation 6. Specifically, let

$$p_{jk} = P\left(u_{ij} > u_{ik} > u_{ix}\right) \ \forall x \neq j, k$$

be the probability that a student ranks school j first and school k second. If the demand model is sufficiently flexible to capture students' substitution patterns, then the predicted probability of ranking *both* j first and k second should closely match the realized rates. To avoid concerns with overfitting, I estimate demand parameters for this exercise on a random hold-out sample of students.[6] Figure 1 plots the correlation between the empirical p_{jk} and the model's predictions. The R squared between actual choice shares and the model's predictions range between .756 for high schools and .819 for elementary schools. Furthermore, the slope between the two measures is close to 1. To assess the importance of microdata, I also replicate the exercise while removing all individual heterogeneity from the multinomial logit model. Consistent with the restrictiveness of the IIA property, the corresponding model estimates in Figure A.2 are generally unable to rationalize the most popular choice combinations observed in the data.

[6]Given that the model is estimated from a subsample, it will also be subject to great estimation error than the baseline demand estimates that are estimated on the entire sample of students.

4.2 School supply and assignment mechanism

To fully characterize the model, I need to observe N_j, the capacity constraint for each school. However, capacities are difficult to observe, and may not be rigidly binding at some schools.[7] Instead, I calculate a lower bound for school capacities using the assignment data. If a school's offers were rationed in the assignment process, then that school's capacity is the total number of offers it gave. If seats were not rationed, I assume that the school's capacity is not binding at the margin. This assumption is sufficient for calculating the school's expected enrollment response for *small* changes in utility, which corresponds to our estimand of interest. But it is important to highlight that better data on capacities would be important for assessing any large counterfactual changes.

The assignment process that coordinates offers across schools is the standard student-proposing deferred acceptance algorithm. Each student is initially assigned priorities at each school based on the student's location and characteristics, as well as a random tiebreaking number (in the case two students have the same priority at a school). The algorithm proceeds in rounds. In each round,

1. All unassigned students apply to their most preferred option from the set of schools where they have not been rejected

2. Schools rank all current applications and tentatively accepted students. If the total number of students exceeds a school's capacity, the school rejects candidates with the lowest priorities and tentatively accepts the rest.

The algorithm ends when all students either are tentatively assigned to a school or exhausted their rank order lists. At that point, all tentative matches are then finalized, and any remaining students and seats remain unassigned.

Since I observe all the inputs to the assignment process as well as the assignment algorithm, it is straightforward to replicate the match process under the submitted rank choices or any counterfactual rankings. In most years, I can nearly completely replicate the match based on the data that I observe. However, in the first year of the match, my data is less complete — I observe data from a combination of the main match and a supplementary round. I do not have the data necessary to separate the rankings and outcomes for the main round and the supplementary round. Nevertheless, by running the student-proposing deferred acceptance algorithm on the rank ordering and priorities that I do observe, I can still replicate realized offers for 90% of all students. As a result, I treat the imperfect data as a reasonable approximation of the true match process in 2012.

The assignment process is at the *program* level, and students may be matched to different programs within the school based on their eligibility, seat preferences, and program preferences. However, most of my data and outcomes are at the higher *school* level. As a result, I make an additional simplifying restriction where I abstract from the smaller programs within a school, and I treat the ranking and assignment process as occurring at the school level. Figure A.3 compares the share of student assignments that are replicated using school-level choices and priorities to the share of assignments that are replicated using program-level choices and priorities. The replication rate falls by less than 5% after aggregating the options to the school level.

[7] For example, neighborhood schools are required to serve all students in their area.

4.3 Validation

I have made simplifying assumptions to implement each part of the market model. To assess whether the model can capture the core outcomes in the market, I test whether the model's predicted *offer* shares for each school match their empirical counterparts. This is more demanding than the individual tests that have been presented so far since it requires the *combination* of all three components of the market to be approximately correct. Moreover, the test implicitly places the most weight on fitting the features that are most relevant for outcomes (for example, predicting a student's top choice is particularly important if the student has a high priority, whereas predicting a student's later choices is particularly important if the student has a low priority). As a result, the test may be a particularly useful comprehensive assessment of the model's fit.

Figure 2 plots the empirical offer share for each school against the model's average predicted offer share after simulating the market 100 times. In each simulation, I draw idiosyncratic taste shocks for each student-school pair from the assumed type I extreme value distribution. I then rank schools according to each student's realized utilities and run the assignment algorithm while taking the student's lottery number, school priorities, and school capacities as given. To ensure that my results are not driven by overfitting, I again estimate demand parameters from a randomly selected holdout sample, and I simulate the market using the remaining students.[8] I find that schools' predicted offer shares are tightly correlated with schools' actual offer shares, even for schools that are not at capacity, which is particularly reassuring that I have captured the key components of the assignment process. The notable exception is that elementary school students are less likely to be unassigned in my simulations than in reality, which may reflect some measurement error in the neighborhood priorities given to students. Even in the elementary school case, though, empirical offer shares closely match estimated offer shares, so the excess assigned students do not appear to benefit any school in particular.

5 Estimates of competitive pressure

The key estimand is each school's semi-elasticity of enrollment with respect to its quality.[9] I estimate this semi-elasticity by using the empirical model from Section 4 to simulate enrollment changes when the school's quality term increases.[10] Specifically, for each school j, I estimate e_j by increasing its quality measure V_j by a fixed increment Δ while holding all other schools' qualities fixed at their estimated levels. I then re-simulate the market's offer shares using the same approach as in Section 4.3, where I draw students' idiosyncratic taste shocks from the assumed distribution and run the match separately for students' rank order lists under each simulation draw. It follows that the estimated semi-elasticity is then

$$\hat{e}_j = \frac{\hat{n}_j\left(\hat{V}_j + \Delta, \hat{V}_{-j}\right) - \hat{n}_j\left(\hat{V}_j, \hat{V}_{-j}\right)}{\Delta}, \tag{7}$$

[8] Removing students from the market simulation without adjusting school capacities would create excess capacity at otherwise capacity constrained schools. To address this issue, I reduce the capacities of each school by the number of realized offers given to students in the holdout sample. This ensures that the realized matches for the simulation sample are unaffected by the removal of other students as long as rank-order lists remain the same.

[9] Formally, this measure is defined in Equation 3 as $e_j \equiv \partial \log n_j \left(V_j, V_{-j}\right) / \partial V_j$.

[10] This approach is based on the approach from Bayer and McMillan (2005). I adapt their framework for simulating demand elasticities to the centralized assignment system in my setting.

where $\hat{n}_j(V_j, V_{-j})$ is school j's simulated offer share given school qualities (V_j, V_{-j}). The mechanism is discrete, so there is a bias-variance tradeoff between choosing a large Δ (where the local approximations for capacity become less valid) and choosing a small Δ (where estimation and simulation error may be substantial relative to the actual change in offers shares). I set $\Delta = 1$, which can be interpreted as the preference cost of commuting an extra 1km to school for a white, non-FRL student.

Figure 3 plots the empirical CDF for the estimated school-level enrollment semi-elasticities. Competitive incentives for enrollment are generally low but can be substantial at some schools. I estimate that 32% of schools are already capacity constrained, and have no enrollment-based incentives to improve. These capacity constrained schools also constitute 32% of offers, so capacity constrained schools are not systematically larger or smaller than non-capacity constrained schools. On the other hand, more than half of all schools can expect to enroll at least 8.3% more students if their perceived quality increases by a 1km-equivalent utility increment, so enrollments are far from inelastic. There is a long tail of schools facing particularly high competitive pressure — the 90th percentile of schools can expect to enroll 19.3% more students for the same utility increase. Larger schools have generally less elastic demand, so the distribution of enrollment semi-elasticities are shifted to the left when schools are weighted by the number of offers, but otherwise, the patterns remain comparable.

Table 3 compares my estimates of competitive pressure to traditional concentration-based proxies. The results support the general intuition that competitive pressure is lower in areas with fewer competitors, but also highlight that concentration is not a sufficient statistic for competition. On average, schools with one more competitor within a 5km radius have 0.24pp higher enrollment semi-elasticities, and schools with a 10% higher market share among students living within a 5km radius of the school have 0.38pp lower enrollment semi-elasticities. However, while concentration is negatively correlated with competition, the two are distinct quantities. Even when I include both measures of concentration and allow the coefficients to vary arbitrarily by grade, the adjusted R-squared of the regression of e_j on concentration is less than .04, so more than 95% of the variation in competitive pressure exists conditional on concentration.

To further understand the variation in competitive pressure, I disaggregate the distribution of competitive pressure by school characteristics. Figure 4 plots the density of the competitive measure by the sector of the school. As expected, the traditional sector schools generally face the least competitive pressure, whereas alternate sectors like the charter and magnet schools face strong incentives to recruit additional students. Interestingly, although innovation schools were created in the district as alternatives to traditional schools, they do not necessarily face greater competitive pressures than even traditional schools, and they are the most likely to be capacity-constrained. Similarly, Figure 5 plots the density of the competitive measure by the grade level of the school. Elementary schools tend to face more competitive pressure than high schools, whereas middle schools have the largest dispersion between schools with low competitive pressure and schools with high competitive pressure.

6 Relationship between competition and school outcomes

The demand model is agnostic about the content of the quality term V_j. As a result, the competitive pressure term e_j captures the school's competitive incentives to provide *any* characteristic that contributes to students' common utility V_j. To better understand the specific margins of school responses to competition, I use two complementary approaches to test for the effects of competition on school outcomes. The first approach makes cross sectional comparisons between schools, and the second approach makes within-school comparisons following a policy change. I find consistent conclusions across both approaches: competition alone does not lead to substantial increases in school effectiveness, but it does induce schools to devote discretionary funding towards instruction rather than administration.

6.1 Cross sectional variation

As a starting point, I consider the cross sectional difference in school inputs and outputs between observably similar schools that face different degrees of competitive pressure. To do so, I estimate the school level regression

$$y_j = \beta e_j + \theta X_j + \nu_j, \tag{8}$$

where e_j is the school's competitive pressure, and X_j is a set of controls for the size, average student composition, and sector of the school. To ensure that I am capturing the effects of competition, I focus on examining school outcomes after the introduction of centralized assignment in 2012. The key identifying assumption for the causal effect of competitive pressure on school outcomes is that

$$E\left[e_j \nu_j\right] = 0, \tag{9}$$

so a school's competitive pressure is uncorrelated with other unobserved factors that also contribute to the outcome (ν_j). This is a strong assumption. For example, schools in competitive areas may also be more likely to enroll students whose parents closely monitor school principals and teachers. To assess the potential concerns with student sorting or other omitted variables, I use value-added as my measure of school effectiveness rather than test scores to control for student sorting. I also systematically probe the robustness of my results to including additional controls (in the spirit of Altonji et al., 2005; Oster, 2019).[11]

Table 4 reports estimates of β across a variety of specifications. I find that schools facing higher competition are not more effective at increasing test scores. Without controls, a 10 percentage point increase in competitive pressure e_j is correlated with a .015 (0.013 s.e.) standard deviation *decrease* in value-added.[12] This negative relationship becomes slightly smaller in magnitude after including controls for average student characteristics and the sector of the school but remains negative and statistically indistinguishable from 0.[13] If there is omitted variables bias in Equation 8 that is obscuring the effects of competitive pressure on school effectiveness, it would have to be mostly uncorrelated with the observable characteristics of the school and bias β downwards. In other

[11]Note, however, that the addition of controls in this setting is not innocuous. There is a separate concern that student composition or size reflect equilibrium outcomes, so controlling for them may also *introduce* bias (Angrist and Pischke, 2009).

[12]The results also remain similar when I include schools whose capacities bind, although the interpretation of the estimates becomes more complicated. In the model, the relationship between competitive pressure and school quality only holds for schools that are below capacity. Equation 4 highlights that capacity constrained schools may face strong incentives to raise quality to the point where their capacities bind, but no incentives to further increase quality.

[13]The district places some underperforming schools under "targeted interventions," which provides additional support to try to turn around their performance. There is some uncertainty about whether these interventions are a confounder or an outcome of school competition. I drop all schools that receive interventions from the district at any point in the sample period in the last column, and my results remain similar.

words, schools facing *less* competition would need to have better unobserved determinants of school effectiveness.

On the other hand, I find that schools facing greater competitive pressure do spend more on instruction. Without controls, a 10 percentage point increase in competitive pressure e_j is correlated with a 2.1pp (0.9 s.e.) increase in the share of a school's discretionary budget spent on instruction. This relationship also remains stable after including controls even though the adjusted R^2 of the regression increases substantially. It is also worth highlighting that in the alternate model from Section 3, larger schools should face lower fixed costs and devote more money to instruction. Since larger schools also generally face less competitive pressure, this should bias the coefficient on competitive pressure (β) downwards. Although the fact that the coefficient increased from .214 to .247 after controlling for school size provides some support for this explanation, the small magnitude of the change suggests that fixed costs are not the primary explanations for differences in schools' spending decisions.

6.2 Variation from centralized assignment

Although cross sectional comparisons are a useful baseline, it is ultimately difficult to reject the possibility that schools facing greater competitive pressure are different in unobservable ways. As a complementary exercise, I use the introduction of centralized assignment as exogenous variation in schools' competitive environments and consider the within-school change in inputs and outputs. My event-study estimation equation is

$$y_{jt} = \sum_t \beta_t \left(e_j \times I_t\right) + \alpha_j + \gamma_{gt} + \theta X_{jt} + \eta_{jt}, \tag{10}$$

where e_j is the school's estimated competition measure, I_t is an indicator for year t, α_j is a school fixed effect, γ_{gt} are time fixed effects (that vary by group g), and X_{jt} are additional controls for the school's composition of students. In the baseline specification, I allow for differential trends by the sector of the school, but I do not control for the composition of students at the school (to allow for the possibility that student composition is an outcome of the policy). The key identifying assumption for β_t is that

$$E\left[e_j \eta_{jt}\right] = 0, \tag{11}$$

so schools facing greater competitive pressure are not experiencing any changes to their school outcomes that are not explained by the observable controls.[14]

I find results that are consistent with the cross sectional results. Figure 6 reports the event-study coefficients for the outcome of school value-added. High and low elasticity schools appear to be on similar trends before the introduction of the match, which bolsters the interpretation of β_t as the causal effect of increasing competitive pressure on schools. I do not find any evidence that schools facing more competition increased their effectiveness following the introduction of centralized assignment, and if anything, the point estimates are generally negative. A school with a 10p.p. higher

[14]Note that although the identification assumptions for this approach is weaker, interpreting β_t as the effects of competition also requires that centralized assignment particularly increased competitive pressure at high e_j schools. This additional assumption would be satisfied, for example, if opting out of neighborhood schools was uniformly difficult. On the other hand, this additional assumption may be violated if parents were able to freely choose competitive schools even before centralized assignment.

competitive pressure *lowered* its value-added by 0.012 (0.015 s.e.) standard deviations following the introduction of centralized assignment.

Table 5 summarizes the pooled differences in differences estimates across a variety of robustness checks that rule out other potential identification concerns. For example, the state exam that is the basis of my value-added estimates changed its format for high school students after 2014. Although I standardize test scores each year into standard deviations, there may be a concern that different schools are differentially affected by the new exam format. When I drop results after 2014, the estimate becomes positive, but remains small in magnitude and statistically indistinguishable from zero. The effects are also similar if I exclude targeted intervention schools, so my results are not explained by policies that the district may have introduced to turn around some underperforming schools.

On the other hand, I do find that the share of expenditures that are dedicated to instruction increases at schools facing high competitive pressure. Table 5 also reports the coefficients from estimating Equation 10 on the outcome of instructional expenditure shares at the school. I find that schools facing a 10p.p. higher competitive pressure increases their instructional spending shares by 1.8 percentage points (0.84 s.e.) following the introduction of centralized assignment. These effects also remain similar across specifications, so they do not appear to be driven by changes in student composition or subsequent policy changes.[15]

7 Conclusion

I use a novel method to directly measure schools' competitive incentives and draw two conclusions. First, the distribution of competitive pressure is dispersed within a public school district. A third of schools face no additional incentives to increase enrollment on the margin, but at least a quarter of schools, including those in the traditional sector, face substantial incentives to attract more students. Second, schools respond to competitive pressure by shifting expenditures from administration to instruction, but they do not appear to increase their school *effectiveness* on academic achievement.

The results in this paper focus on a single, large school district in the U.S., and may not be representative of effects in other institutional settings or contexts. However, it is worth highlighting that at least within public school districts in the U.S., the district in question is unusually decentralized and flexible. The results are therefore likely to be close to the upper bound of plausible competitive effects within large U.S. districts where the possibility of expanding choice is especially relevant. Moreover, the approach in this paper can be implemented in other school districts with a centralized assignment mechanism, and it would be useful to assess the extent to which competitive pressures and their effects differ in other districts.

Finally, there are also several other fruitful avenues for future research. It would be useful to more comprehensively consider students' outside options, either to other school districts or private schools to assess the degree to which schools may also be responding to students' decisions to leave the district altogether. Another key direction is to better understand the school's supply function. Schools may respond through increasing instructional spending rather than school effectiveness because changing the latter is either difficult or simply unprofitable. Disentangling these two possible explanations

[15]Given that the per-student funding for the school depends on student characteristics, the stability of estimates after I explicitly control for student composition is particularly reassuring that the results are mechanically determined by any enrollment changes.

would be crucial for the design of policy that can ensure that students ultimately benefit from competition.

References

Abdulkadiroglu, A., Agarwal, N., Pathak, P. A. 2017a. The Welfare Effects of Coordinated Assignment: Evidence from the New York City High School Match. American Economic Review. 107 (12), 3635–3689.

Abdulkadiroglu, A., Pathak, P. A., Schellenberg, J., Walters, C. R. 2017b. Do Parents Value School Effectiveness? Working Paper 23912, National Bureau of Economic Research.

Agarwal, N., Somaini, P. 2019. Revealed Preference Analysis of School Choice Models.Technical Report w26568, National Bureau of Economic Research, Cambridge, MA.

Allende, C. 2019. Competition Under Social Interactions and the Design of Education Policies. 104.

Altonji, J. G., Elder, T. E., Taber, C. R. 2005. Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools. Journal of Political Economy. 113 (1), 151–184.

Angrist, J. D., Pischke, J.-S. 2009. Mostly Harmless Econometrics: An Empiricist's Companion. Princeton, Princeton University Press, 1st edition.

Bayer, P., McMillan, R. 2005. Choice and Competition in Local Education Markets.Technical Report w11802, National Bureau of Economic Research, Cambridge, MA.

Berry, S., Levinsohn, J., Pakes, A. 2004. Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market. Journal of Political Economy. 112 (1), 68–105.

Bresnahan, T. F. 1989. Chapter 17 Empirical studies of industries with market power. In Handbook of Industrial Organization. 2, 1011–1057, Elsevier.

Campos, C., Kearns, C. 2022. The Impact of Neighborhood School Choice: Evidence From Los Angeles' Zones of Choice. 96.

Card, D., Dooley, M. D., Payne, A. A. 2010. School Competition and Efficiency with Publicly Funded Catholic Schools. American Economic Journal: Applied Economics. 2 (4), 150–176.

Chetty, R., Friedman, J. N., Rockoff, J. E. 2014. Measuring the Impacts of Teachers I: Evaluating Bias in Teacher Value-Added Estimates. American Economic Review. 104 (9), 2593–2632.

Dafny, L. S. 2005. How Do Hospitals Respond to Price Changes? American Economic Review. 95 (5), 1525–1547.

Duggan, M. G. 2000. Hospital Ownership and Public Medical Spending. The Quarterly Journal of Economics. 115 (4), 1343–1373.

Epple, D., Romano, R. E., Urquiola, M. 2017. School Vouchers: A Survey of the Economics Literature. Journal of Economic Literature. 55 (2), 441–492.

Fan, Y. 2013. Ownership Consolidation and Product Characteristics: A Study of the US Daily Newspaper Market. American Economic Review. 103 (5), 1598–1628.

Figlio, D., Hart, C. M. D. 2014. Competitive Effects of Means-Tested School Vouchers. American Economic Journal: Applied Economics. 6 (1), 133–156.

Friedman, M. 1962. Capitalism and Freedom. University of Chicago Press.

Gale, D., Shapley, L. S. 1962. College Admissions and the Stability of Marriage. The American Mathematical Monthly. 69 (1), 9–15.

Gilraine, M., Petronijevic, U., Singleton, J. D. 2021. Horizontal Differentiation and the Policy Effect of Charter Schools. American Economic Journal: Economic Policy. 13 (3), 239–276.

Glaeser, E. L., Shleifer, A. 2001. Not-for-profit entrepreneurs. Journal of Public Economics. 81 (1), 99–115.

Goodreau, S. M., Kitts, J. A., Morris, M. 2009. Birds of a feather, or friend of a friend? using exponential random graph models to investigate adolescent social networks*. Demography. 46 (1), 103–125.

Guajardo, J. A., Cohen, M. A., Netessine, S. 2016. Service Competition and Product Quality in the U.S. Automobile Industry. Management Science. 62 (7), 1860–1877.

Hastings, J. S., Kane, T. J., Staiger, D. O. 2008. Heterogeneous Preferences and the Efficacy of Public School Choice.

Hausman, J. A., Ruud, P. A. 1987. Specifying and testing econometric models for rank-ordered data. Journal of Econometrics. 34 (1), 83–104.

Hoxby, C. M. 2000. Does Competition among Public Schools Benefit Students and Taxpayers? The American Economic Review. 90 (5), 1209–1238.

Hoxby, C. M. ed. 2003. The economics of school choice. A National Bureau of Economic Research conference report, Chicago, University of Chicago Press.

Hsieh, C.-T., Urquiola, M. 2006. The effects of generalized school choice on achievement and stratification: Evidence from Chile's voucher program. Journal of Public Economics. 90 (8), 1477–1503.

Idoux, C. 2022. Integrating New York City Schools: The Role of Admission Criteria and Family Preferences. 100.

Ito, K., Sallee, J. M. 2018. The Economics of Attribute-Based Regulation: Theory and Evidence from Fuel Economy Standards. The Review of Economics and Statistics. 100 (2), 319–336.

Kornai, J., Maskin, E., Roland, G. 2003. Understanding the Soft Budget Constraint. Journal of Economic Literature. 41 (4), 1095–1136.

McMillan, R. 2004. Competition, incentives, and public school productivity. Journal of Public Economics. 88 (9), 1871–1892.

Muralidharan, K., Sundararaman, V. 2015. The Aggregate Effect of School Choice: Evidence from a Two-Stage Experiment in India *. The Quarterly Journal of Economics. 130 (3), 1011–1066.

Neilson, C. A. 2021. Targeted Vouchers, Competition Among Schools, and the Academic Achievement of Poor Students.

Oster, E. 2019. Unobservable Selection and Coefficient Stability: Theory and Evidence. Journal of Business & Economic Statistics. 37 (2), 187–204.

Pathak, P. A., Shi, P. 2018. How Well Do Structural Demand Models Work? Counterfactual Predictions in School Choice. SSRN Scholarly Paper ID 3356092, Social Science Research Network, Rochester, NY.

Prince, J. T., Simon, D. H. 2017. The Impact of Mergers on Quality Provision: Evidence from the Airline Industry. The Journal of Industrial Economics. 65 (2), 336–362.

Ridley, M., Terrier, C. 2018. Fiscal and Education Spillovers from Charter School Expansion. Working Paper 25070, National Bureau of Economic Research.

Roth, A. E. 1982. The Economics of Matching: Stability and Incentives. Mathematics of Operations Research. 7 (4), 617–628.

Rothstein, J. 2007. Does Competition Among Public Schools Benefit Students and Taxpayers? Comment. American Economic Review. 97 (5), 2026–2037.

Sweeting, A. 2013. Dynamic Product Positioning in Differentiated Product Markets: The Effect of Fees for Musical Performance Rights on the Commercial Radio Industry. Econometrica. 81 (5), 1763–1803.

Urquiola, M. 2016. Competition Among Schools. In Handbook of the Economics of Education. 5, 209–237, Elsevier.

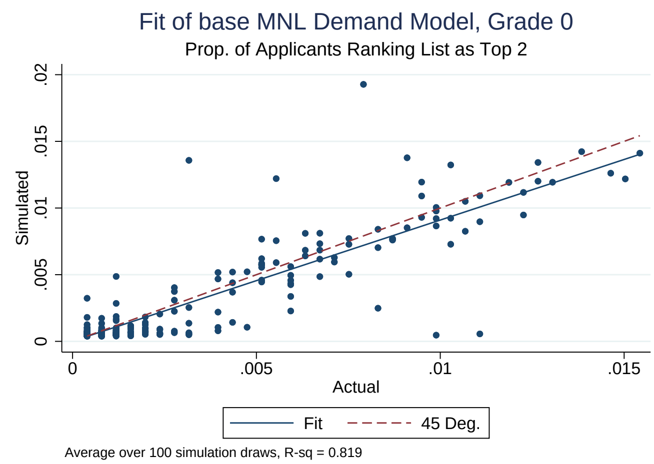
Walters, C. R. 2018. The Demand for Effective Charter Schools. Journal of Political Economy. 126 (6), 2179–2223.

Whitehurst, G. J. R. 2017. The 2016 Education Choice and Competition Index.

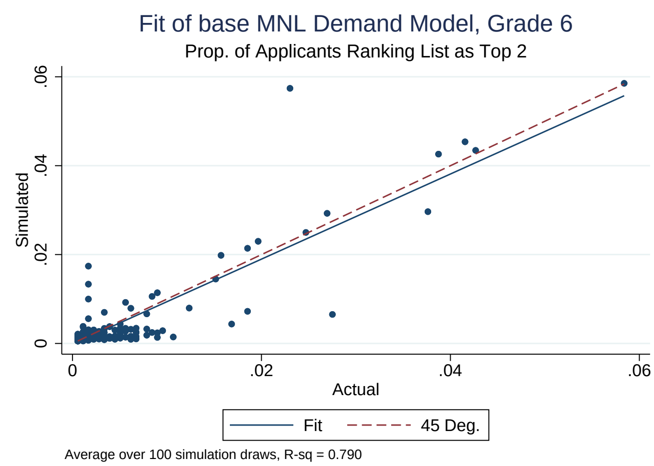
Tables and figures

Figure 1: Model fit: substitution patterns

(a) Elementary schools



(b) Middle schools



(c) High schools

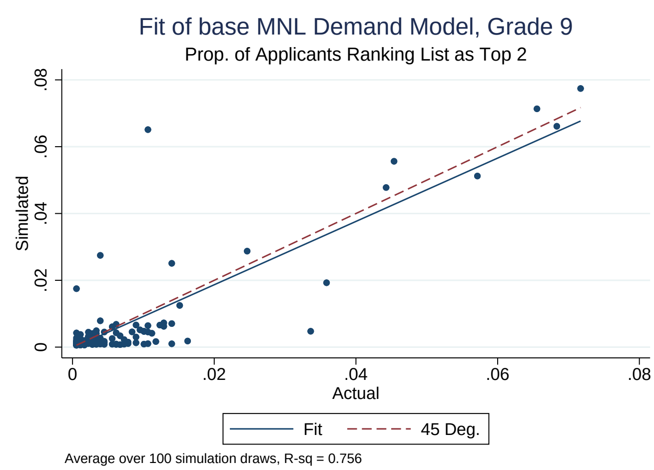
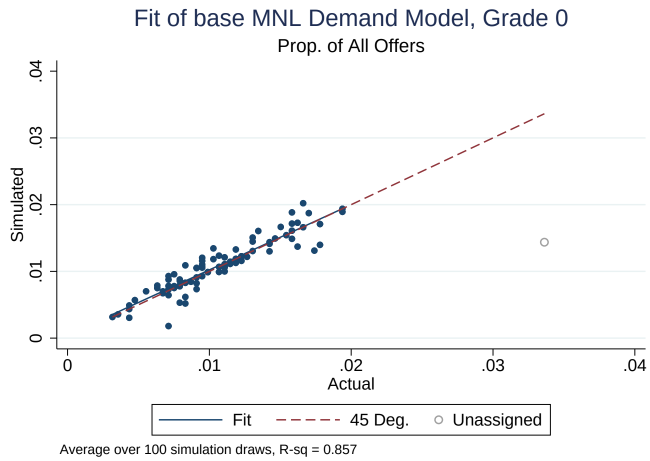
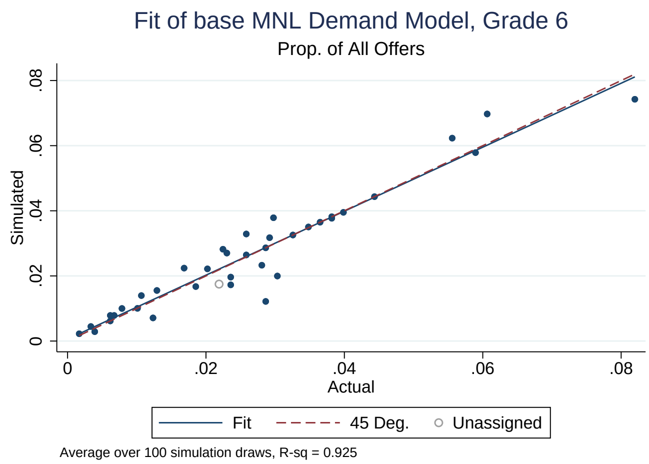


Figure 2: Model fit: offer shares

(a) Elementary schools



(b) Middle schools



(c) High schools

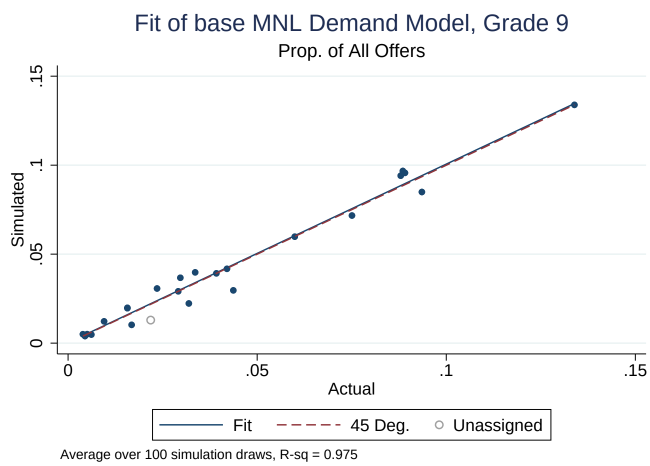
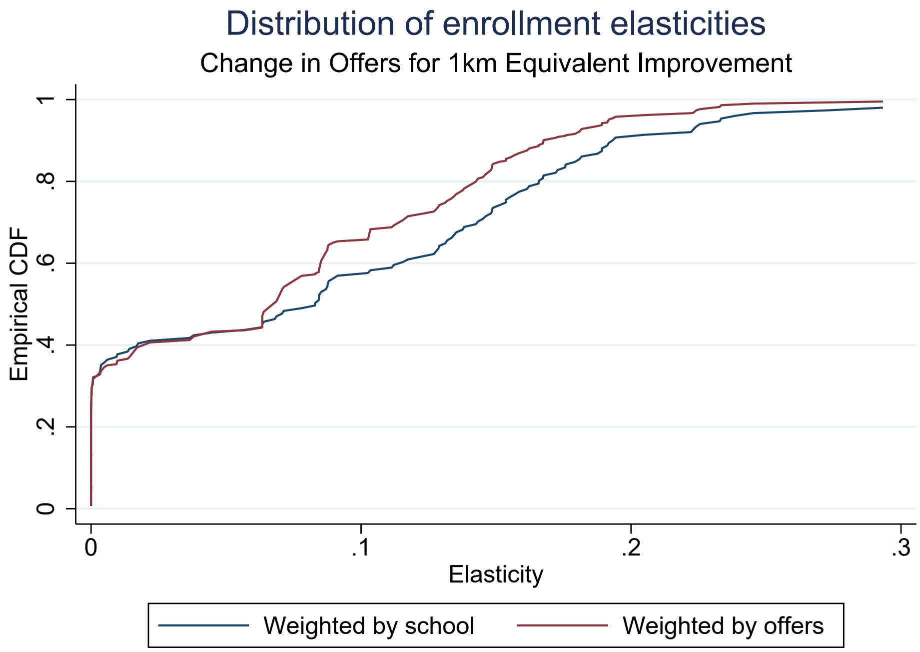
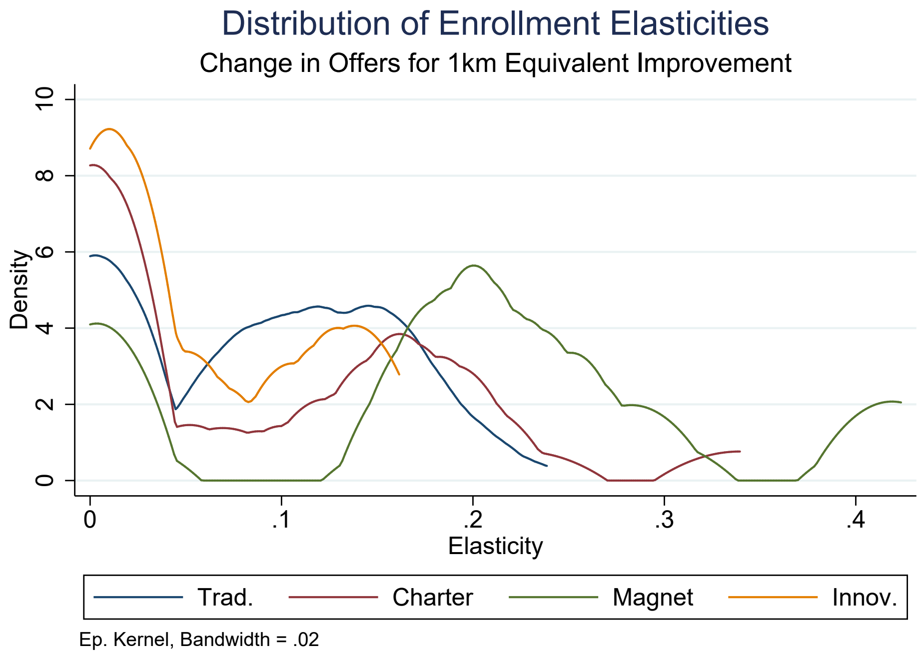


Figure 3: Distribution of competitive pressure



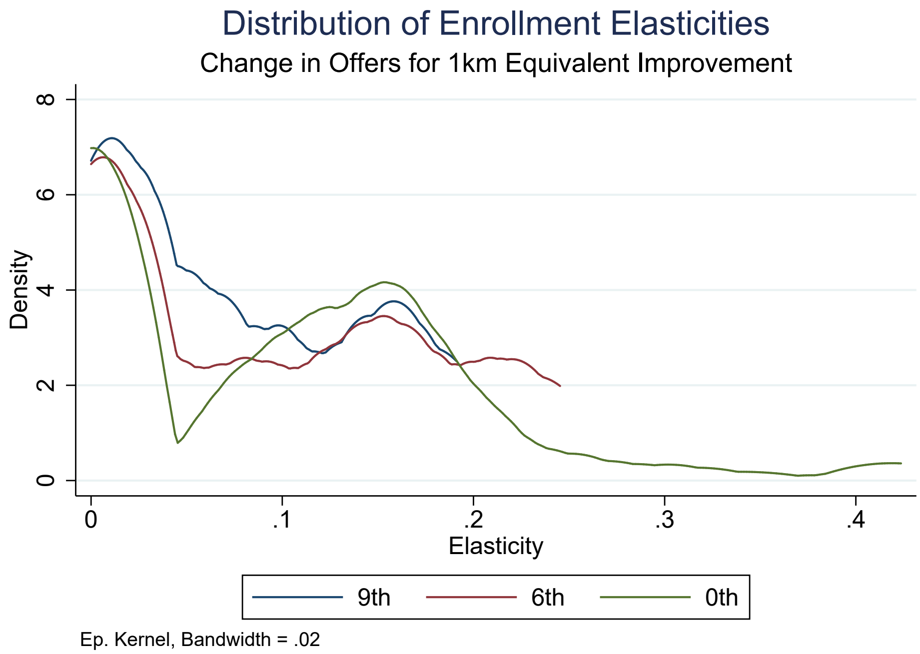
Note: The figure plots the empirical CDF of the school-level estimates of Equation 7, the semi-elasticity of enrollment with respect to school quality. Intuitively, the measure captures the school's expected increase in enrollment after a utility increase equivalent to the costs of a 1km commute change. The blue series weights all schools equally, while the red series weights each school by the number of students it enrolls through the assignment process.

Figure 4: Competitive pressure by sector



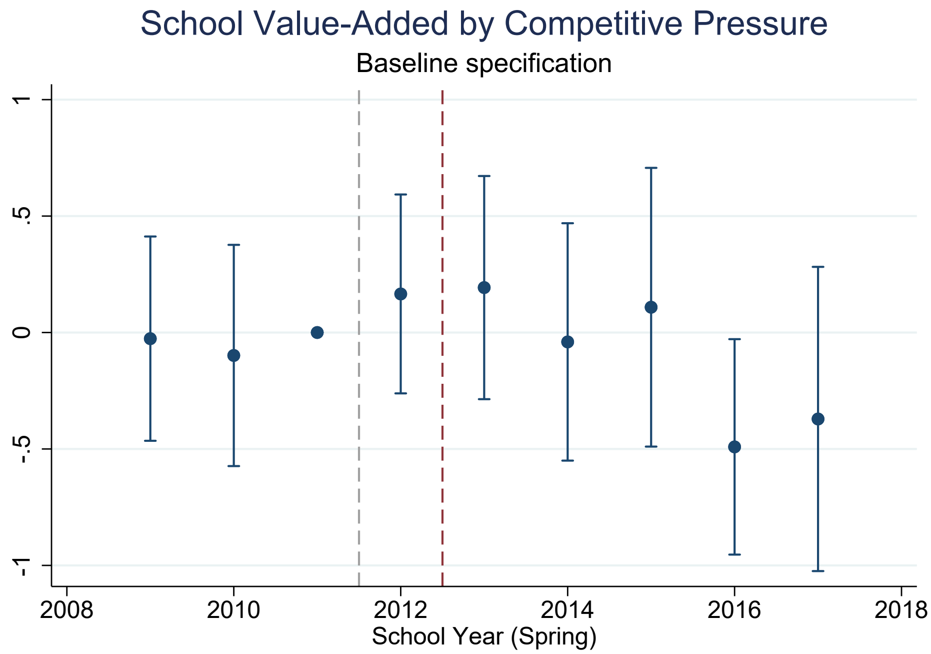
Note: The figure plots the kernel density of the school-level estimates of Equation 7, the semi-elasticity of enrollment with respect to school quality, separately for each sector in the district.

Figure 5: Competitive pressure by grade



Note: The figure plots the kernel density of the school-level estimates of Equation 7, the semi-elasticity of enrollment with respect to school quality, separately by the school's entry grade. 9th grade is the entry grade for high schools. 6th grade is the entry grade for middle schools. 0th grade (i.e., kindergarten) is the entry grade to elementary schools.

Figure 6: Event study coefficients for school effectiveness



Note: The figure plots event study coefficients from estimating Equation 10 on the baseline sample of all schools with estimated competition semi-elasticities e_j and value-added estimates. The coefficients are differential changes in the school's annual value-added estimates by the school's competitive pressure e_j. The outcome is the school's value-added on state exams, estimated from a student-level value-added model. The scale of the value-added estimates is standardized to test score standard deviations. Standard errors are clustered at the school level, and bars indicate the 95% confidence interval.

Table 1: Summary statistics

	Sample period	
	2009-2017	2012
Number of students	181811	81870
Number of schools	256	186
Student shares:		
Black	0.143	0.145
Hispanic	0.567	0.580
ELL	0.234	0.225
Gifted	0.117	0.119
Free/Reduced Lunch	0.707	0.725
Female	0.491	0.493
School characteristics:		
Enrollment	440.4	440.2
	[299.1]	[309.7]
Traditional	0.477	0.511
Innovation	0.151	0.135
Charter	0.192	0.163
Magnet	0.0793	0.0899

Table 2: Demand estimates

	Grade		
	0th	6th	9th
Neighborhood school	2.960***	2.629***	2.369***
	(0.0354)	(0.0410)	(0.0391)
Sibling priority	5.617***	4.938***	4.524***
	(0.116)	(0.188)	(0.178)
Distance (km)	-0.366***	-0.222***	-0.170***
	(0.00925)	(0.00848)	(0.00870)
Black × Dist.	0.0696***	0.0379***	0.0921***
	(0.0146)	(0.0135)	(0.00994)
Hispanic × Dist.	-0.0189	-0.0535***	-0.0240**
	(0.0123)	(0.0113)	(0.00957)
FRL × Dist.	-0.00422	-0.0366***	-0.0360***
	(0.0112)	(0.0108)	(0.00812)
Black × Share Black	3.604***	0.626	1.468***
	(0.298)	(0.412)	(0.389)
Hispanic × Share Hispanic	2.734***	2.340***	2.290***
	(0.149)	(0.159)	(0.162)
ELL × Share ELL	1.575***	1.101***	1.858***
	(0.277)	(0.184)	(0.288)
Gifted × Average achievement	0.920***	0.578***	0.740***
	(0.210)	(0.0838)	(0.0994)
FRL × Average achievement	-1.297***	-1.047***	-0.864***
	(0.0887)	(0.0918)	(0.0990)
Number of ranks	453635	135864	82777
Number of students	4985	3672	3599
Log-likelihood	-15921.3	-13576.4	-12069.8
Pseudo R^2	0.612	0.512	0.513

Note: The table reports parameter models from estimating Equation 1 using students' submitted ranked order lists. The model is an exploded logit model and the parameters are estimated by maximum likelihood. The first two rows are explanatory variables for whether the school is the student's assigned neighborhood school, and whether the student has a sibling attending the school. The final five rows are interactions between student characteristics and average school characteristics. The model is separately estimated by each entry grade. 9th grade is the entry grade for high schools. 6th grade is the entry grade for middle schools. 0th grade (i.e., kindergarten) is the entry grade to elementary schools. Standard errors are in parentheses. Stars indicate the level of significance: * 10%, ** 5%, and *** 1%.

Table 3: Relationship between competitive pressure and concentration

	Outcome: competitive pressure (e_j)					
	(1)	(2)	(3)	(4)	(5)	(6)
Number of schools	0.00902***	0.00238***	0.000761**			
	(0.00310)	(0.000841)	(0.000340)			
Enrollment share				-0.0383*	-0.185***	-0.392***
				(0.0220)	(0.0509)	(0.124)
Market radius	2km	5km	10km	2km	5km	10km
Number of obs.	151	151	151	151	151	151
Adjusted R^2	0.0476	0.0447	0.0262	0.00859	0.0347	0.0288

Note: The table reports bivariate regressions of competitive pressure on school-level measures of local concentration. The first row is the number of other schools within a given radius that are serving the same grades. The second row is the share of students living within a given radius and within the school's grade range that are currently attending the school. Stars indicate the level of significance: * 10%, ** 5%, and *** 1%.

Table 4: Cross sectional effects of competitive pressure on school outcomes

(a) School effectiveness

	Outcome: school value-added					
	(1)	(2)	(3)	(4)	(5)	(6)
Competitive pressure (e_j)	-0.152	-0.203	-0.159	-0.1000	-0.00977	-0.0291
	(0.128)	(0.130)	(0.129)	(0.125)	(0.112)	(0.134)
Number of observations	579	579	579	579	277661	509
Number of schools	118	118	118	118	118	104
Adjusted R^2	0.00893	0.0302	0.0430	0.0826	0.118	0.0883
Controls:						
Size and grade		Y	Y	Y	Y	Y
Student composition			Y	Y	Y	Y
School sector				Y	Y	Y
Student-weighted					Y	
Dropping interventions						Y

(b) School spending

	Outcome: share of expenditures on instruction					
	(1)	(2)	(3)	(4)	(5)	(6)
Competitive pressure (e_j)	0.214**	0.247***	0.323***	0.228***	0.232***	0.262***
	(0.0904)	(0.0845)	(0.0622)	(0.0660)	(0.0642)	(0.0755)
Number of observations	217	217	217	217	120974	191
Number of schools	112	112	112	112	112	99
Adjusted R^2	0.0339	0.165	0.339	0.428	0.490	0.420
Controls:						
Size and grade		Y	Y	Y	Y	Y
Student composition			Y	Y	Y	Y
School sector				Y	Y	Y
Student-weighted					Y	
Dropping interventions						Y

Note: The table reports coefficients from estimating Equation 8. The sample is all schools with both outcomes after 2012 and competitive pressure estimates. The school's competitive pressure is estimated from the empirical model of the market in 2012 using Equation 7. The school's value-added on state exams is estimated from a student-level value-added model and allowed to vary arbitrarily by year. Student composition controls are controls for the share of black, Hispanic, ELL, gifted, SPED, free/reduced lunch, and female students at the school. The last column drops schools that, at any point during the sample period, have received additional interventions from the district due to underperformance. Standard errors are in parentheses and clustered at the school-level. Stars indicate the level of significance: * 10%, ** 5%, and *** 1%.

Table 5: Pooled differences in differences estimates

(a) School effectiveness

	Outcome: school value-added					
	(1)	(2)	(3)	(4)	(5)	(6)
Competitive pressure	-0.178	-0.118	-0.2184	0.0646	-0.113	-0.0310
(e_j) × after match	(0.149)	(0.153)	(0.142)	(0.142)	(0.134)	(0.151)
Number of observations	1005	1005	906	661	437544	882
Number of schools	118	118	118	118	118	104
Adjusted R^2	0.243	0.253	0.277	0.343	0.397	0.278
School sector trends		Y	Y	Y	Y	Y
Student controls			Y			
Dropping post 2014				Y		
Student-weighted					Y	
Dropping interventions						Y

(b) School spending

	Outcome: share of expenditures on instruction				
	(1)	(2)	(3)	(4)	(5)
Competitive pressure	0.178*	0.181**	0.197**	0.204***	0.158*
(e_j) × after match	(0.0967)	(0.0842)	(0.0804)	(0.0678)	(0.0856)
Number of observations	322	322	322	180941	283
Number of schools	109	109	109	113	96
Adjusted R^2	0.802	0.806	0.810	0.882	0.827
School sector trends		Y	Y	Y	Y
Student controls			Y		
Student-weighted				Y	
Dropping interventions					Y

Note: The table reports pooled coefficients from estimating Equation 10. The sample is all schools with competitive pressure estimates. The school's competitive pressure is estimated from the empirical model of the market in 2012 using Equation 7. The school's value-added on state exams is estimated from a student-level value-added model and allowed to vary arbitrarily by year. Student controls are controls for the log number of students at the school, as well as the share of black, Hispanic, ELL, gifted, SPED, free/reduced lunch, and female students. The last column drops schools that, at any point during the sample period, have received additional interventions from the district due to underperformance. Standard errors are in parentheses and clustered at the school-level. Stars indicate the level of significance: * 10%, ** 5%, and *** 1%.

A Additional tables and figures

Figure A.1: Number of schools ranked in application

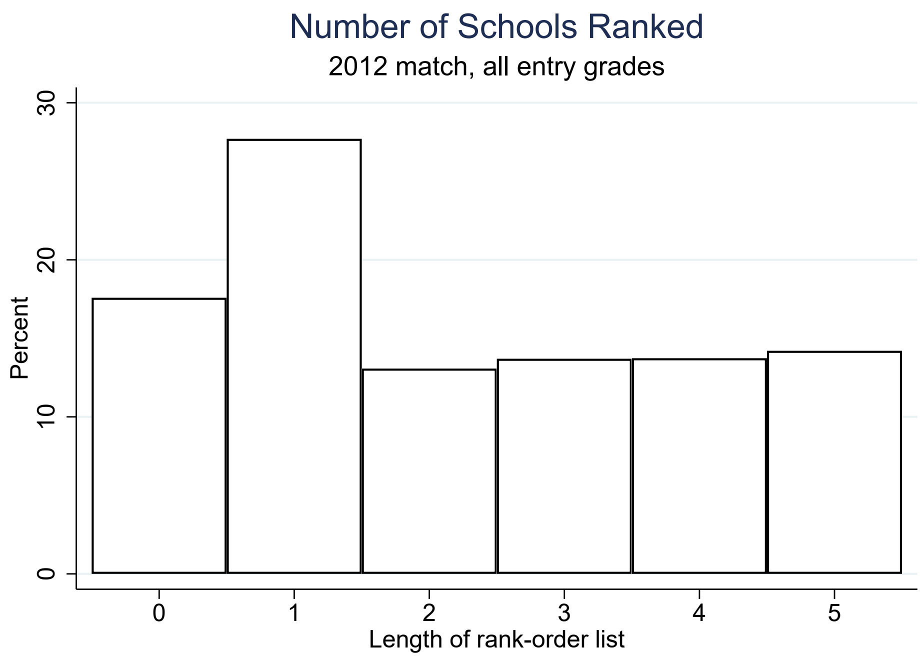
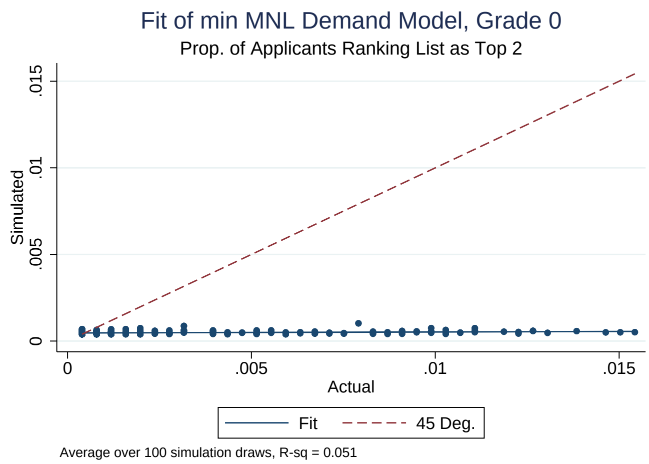
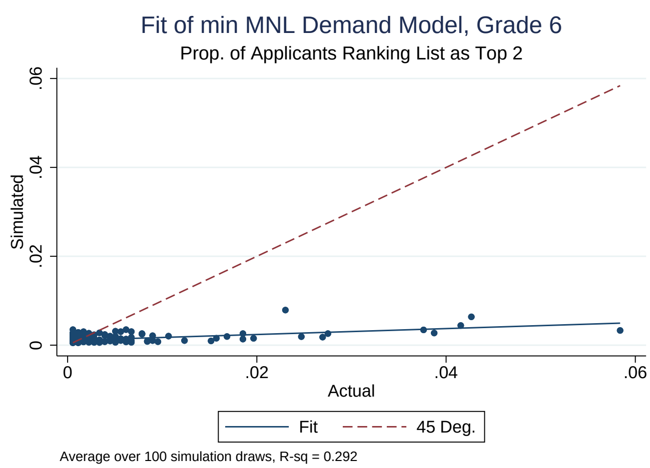


Figure A.2: Substitution patterns (no heterogeneity)

(a) Elementary schools



(b) Middle schools



(c) High schools

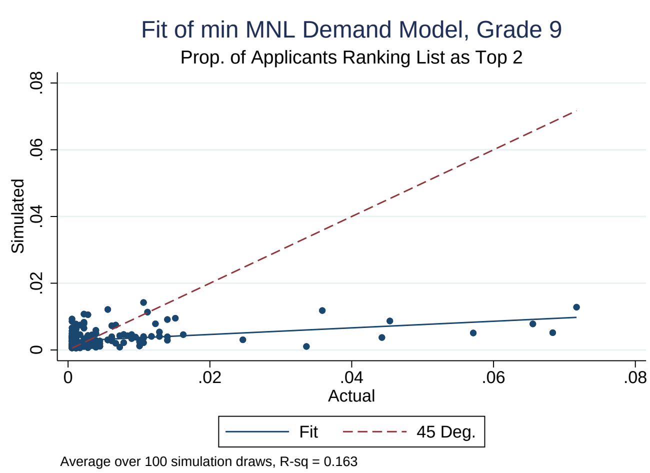


Figure A.3: Match replication rate

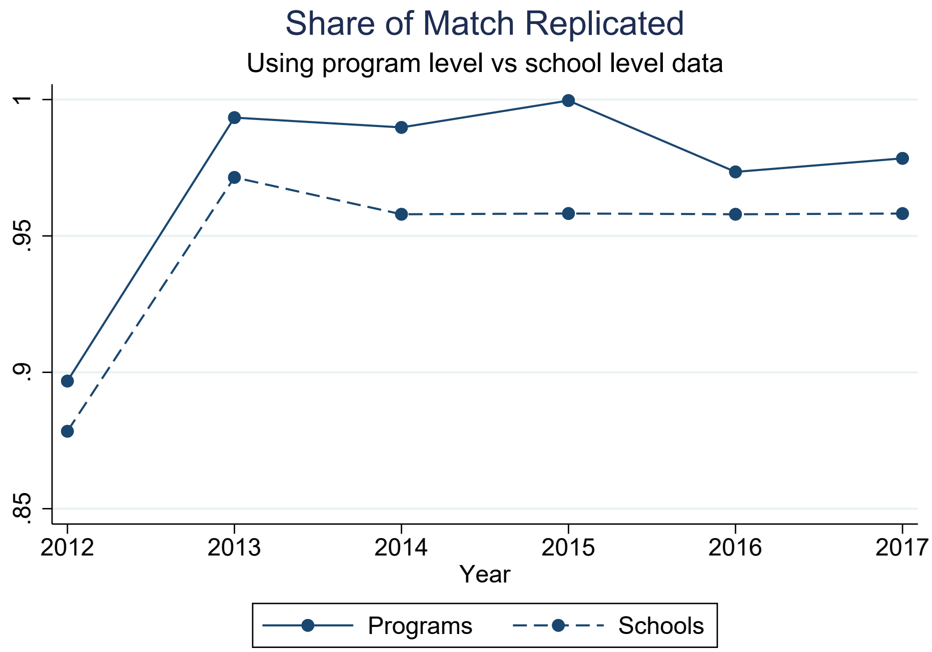
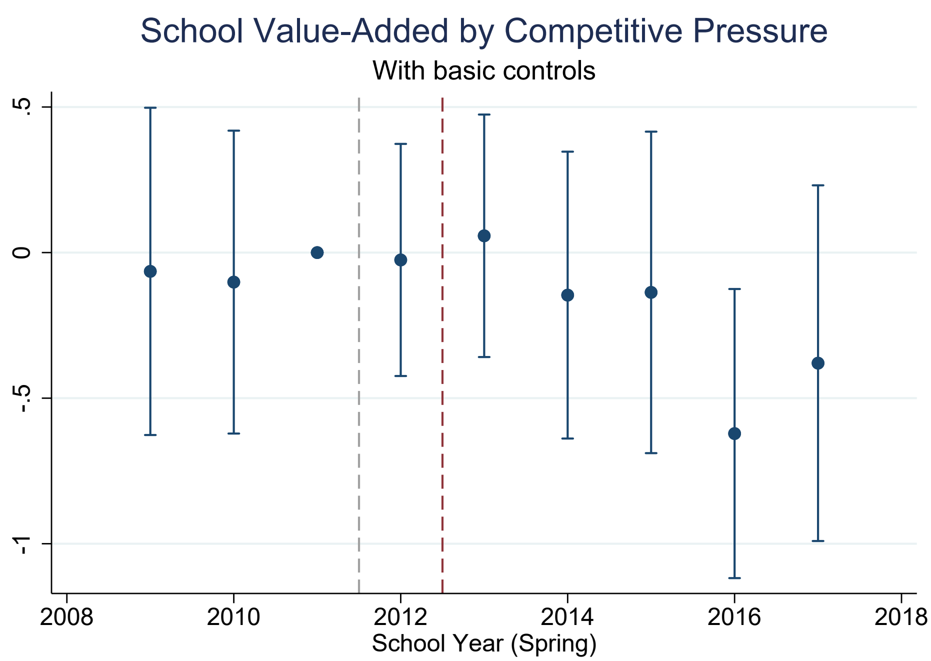


Figure A.4: Event study coefficients (other specifications)

(a) Basic controls



(b) Additional controls