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Market Signals: Evidence on the Determinants and Consequences of School Choice from a Citywide Lottery

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ABSTRACT

We estimate school-choice preferences revealed by the rank-ordered lists submitted by more than 22,000 applicants to a citywide lottery for more than 200 traditional and charter public schools in Washington, DC. The results confirm previously reported findings that commuting distance, school demographics, and academic indicators play important roles in school choice, and that there is considerable heterogeneity of preferences. Simulations suggest segregation by race and income would be reduced and enrollment in high-performing schools increased if policymakers were to expand school choice by relaxing school capacity constraints in individual campuses. The simulations also suggest that closing the lowest-performing schools could further reduce segregation and increase enrollment in high-performing schools.

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I. INTRODUCTION

Role of consumer preferences in school-choice policy

Understanding what parents value when they choose a school for their children is critical for learning how choice-based competition would influence school quality and the sorting of students into schools. Knowing the answer to this question would also help policymakers design the rules that govern public school choice and predict the behavioral implications of policies that could influence enrollment dynamics. Such policies can include opening, closing, or relocating schools. Knowing which parents will respond to which policy change, and in turn how that affects the composition of the school and subsequent choosers' willingness to attend, one can model the long-term effects of policy changes as well as the immediate first-year effects.

The collection of school options policymakers provide to parents and the rules that govern choice, sometimes referred to as "choice architecture" (Thaler and Sunstein 2008), is often viewed as a way policymakers promote individual freedom to choose while nudging choosers toward socially desirable outcomes. These outcomes for school choice are typically social integration (by race and income) and improved academic performance. If choosers are motivated by convenience and nonacademic amenities, then market-based competition will presumably lead to more of those amenities. Conversely, if choosers value academic performance, then choice should lead to competition along that dimension of quality. A third possibility is that when parents choose a school, they are really choosing a peer group. This would have its own implication for policy. Small policy nudges, such as changing in the way schools are advertised to the public, can induce a few choosers to switch, which would change the makeup of the schools, and ultimately lead to very different sorting equilibria than the status quo. Armed with information about how parents choose schools, policymakers could modify the choice architecture to increase the chances of achieving any goals over the status quo.

In this paper, we empirically estimate these preference parameters and explore how they vary among types of consumers. To do this, we take advantage of a unified school lottery system in Washington, DC that began in 2014. This system centralized an already-robust system of school choice that dated back to 1996, when legislation authorized charter schools and choice among traditional district schools.[1] The new common school-choice lottery gave parents the opportunity to apply to any public school in the city (including both charters and traditional schools) through a centralized assignment process, submitting rank-ordered lists of their most-preferred schools. This process has not only decreased the cost of applying to multiple schools, but has also decreased search and information costs by providing an online school shopping and application portal that contains a searchable index of profiles for participating schools.

In the years leading up to the launch of the common lottery, families in this setting faced a great deal of choice. The public schools include more than 100 schools in the traditional system, the District of Columbia Public Schools (DCPS), and nearly 100 charter school campuses that

[1] The charter-school sector has a substantial market share in DC. By 2010, 40 percent of public school students were in charter schools.

are operated independently and overseen by a charter authorizing board.[2] We compiled a rich dataset that describes both the schools and the choosers, which we merged with the data on how each chooser ranked each school. With these data, we estimated a rank-ordered logit model to infer the preference weights that led parents to rank schools the way they did.

Our additional goal in this paper is to show how these taste parameters can be used to model the effects of changes to the choice sets or choice rules on sorting and academic performance.[3] For example, if DC were to close the lowest-performing schools, what effect would that have on average achievement and how would choosers sort themselves?

Previous research

A common approach to studying how parents choose schools is to ask them directly through surveys (Armor and Peiser 1998; Schneider et al. 1998; Vanourek, Manno, and Finn 1998; Collins and Snell 2000; Kleitz et al. 2000). Despite differences in school-choice contexts and framing of school attributes, these studies share common findings that parents' stated preferences suggest school academic quality is the most important factor in exercising school choice. Moreover, stated preferences for academic quality are robust across income and ethnic groups. This self-reported preference approach has the obvious disadvantage that survey respondents might provide socially desirable responses that do not reflect true preferences (Stein, Goldring, and Cravens 2010). Even carefully worded surveys might not elicit the desired information because choosers may not be fully conscious of all the preferences and biases that guide their own decisions (Arkes and Tetlock 2004; Nosek et al. 2007; Quillian 2008).

The alternative to self-reports is revealed preference. Researchers have used internet searches to gauge parental interest in topics (Schneider and Buckley 2002) as well as enrollment patterns (Fossey 1994; Armor and Peiser 1998; Stein et al. 2010). In contrast to findings from stated preferences, studies using revealed preferences find differences along household income, ethnicity, and student achievement in terms of what school attributes are more highly valued. Specifically, they find that households with higher levels of income, parents' education, and student achievement are more likely to exercise school choice and place more importance on schools' test scores and student body composition. Still, others have used housing markets as a framework to infer the value of a school (Black 1999; Bayer, Ferreira, and McMillan 2007) or of school quality measures like value added (Imberman and Lovenheim 2016).

Rothstein (2006) indirectly tests whether parents prefer more effective schools by investigating the relationship between inter-district school choice and peer quality. He finds no evidence that performance gaps between highly and less desirable schools are meaningfully different in markets with increased school choice. Jacob and Lefgren (2007) analyze parent requests for teachers to infer which teacher characteristics are valued. They estimated teachers'

[2] The number of schools available to any given student depends on the grade level. The greatest number of alternatives is available at the elementary level and the fewest number of alternatives is available at the high school level, where students are concentrated in fewer, larger schools.

[3] We make simplistic assumptions about the way in which choice leads to improved academic outcomes. A more sophisticated analysis of supply-side response to competition is outside the scope of this paper. See Cullen et al. (2003), Hastings et al. (2006), and Deming (2011) for work in this area.

impact on test scores as well as principals' perceptions of teachers' performance and used those measures to predict whether the teacher would be requested by parents. The authors found that parents with higher income value principal-reported ability to improve student *satisfaction,* while parents with lower income value principal-reported ability to raise student *achievement.*

The method we used in this paper, estimation of random utility models, is based on parent requests made within a centralized school-assignment process. In these situations, parents have a menu of alternatives, must submit their rank-ordered preferences, and are assigned using an algorithm that tries to satisfy those preferences. Random utility models, which assume that a continuous utility function is used by choosers to rank order items in a choice set, allow us to infer the preference weights that best predict the pattern of submitted rank-ordered choices. One of the first studies based on this method used application data from an open enrollment program in Minneapolis (Glazerman 1998) and found that parents of entering kindergarteners value both academics and race—schools where the chooser's child would not be racially isolated. Hastings, Kane, and Staiger (2005) analyzed rank-ordered lists submitted by families in Charlotte-Mecklenburg, North Carolina, and Harris and Larsen (2015) did so using data from New Orleans. All three studies found that nonacademic factors such as distance and racial composition were key determinants of the schools that families chose, but the studies highlighted different features of consumer demand. The New Orleans study highlighted parental preferences for extra-curricular offerings. They also found that lower-income families had a weaker preference for school academics. The Charlotte-Mecklenburg study explicitly modeled preference heterogeneity via random coefficients and noted that preferences for school academics were stronger for choosers with higher baseline achievement and higher neighborhood income.

Three additional empirical papers from Belgium, England, and the Netherlands use school-choice rankings as well and reach similar conclusions as the U.S. literature. Ruijs and Oosterbeek (2012) estimate conditional logit models of choice in Amsterdam, modeling peer effects by focusing on choices made by elementary students transitioning to middle school. The authors found that choosers prefer schools in close proximity to their homes and schools sought after by same-gender classmates, while indicators of school quality were inconsistent predictors of choice. Burgess et al. (2015) examined choices in England and found, as did most others, that parents prefer schools in close proximity to their homes as well as those with higher socio-economic status (SES). They also found that school academic performance was an important determinant of choice, and that this preference varied by group. However, the authors concluded that the variation in strength of the parameter on academic quality was driven by variation in available choice sets, not by preferences. A more recent working paper by Wouters (2015) estimates conditional logit models using school choice data from the Flemish city of Ghent to estimate the roles of distance, demographics, and school quality in rankings. The author's estimates are largely consistent with earlier literature, showing heterogeneity in preferences for quality. Wouters, however, speculates that this finding is the result of parents having access to more group-dependent information rather than differences in choice sets.

This study's contribution

This paper addresses the following research questions:

- What school attributes do DC families value most when choosing schools?
- How do these preferences vary by type of chooser?
- What do these preferences imply for sorting over time under different policies?

We show in this paper that, consistent with prior literature, parents tend to value convenience (schools close to home, shorter commutes, schools with access to public transit), demographics (schools where applicants are not in a small racial/ethnic minority), and academics (better ratings on accountability indicators or higher proficiency rates, but not higher growth scores). We examined how these preferences varied by chooser race/ethnicity, income, and grade to which the child was applying. For example, white and higher-income applicants to elementary school had stronger preferences about distance and school demographics than African American applicants.

To better understand how demand for school attributes translates into sorting of students under various school-choice policies, we predicted rank-ordered choices and simulated student assignments under different sets of rules and conditions. After each prediction, we calculated the degree of sorting by race and income, summarized by the Index of Dissimilarity (Taueber and Taueber 1976), which varies between zero (groups are evenly distributed across schools) and 100 (groups are perfectly segregated). We note that it is difficult to quantify the effect of choice on academic quality because we do not model the supply-side response, nor do we know much about sorting by a chooser's ability because such measures were not available in our data. However, our simulations suggest that if capacity constraints were lifted in individual campuses, there would be less racial segregation and possibly less segregation by income.[4]

This study has some limitations to keep in mind when interpreting the results. First, the study excludes families who chose not to choose. Families with students entering grades K through 12 had a right to attend neighborhood schools, and families with students returning to their current school or following a school feeder pattern did not have to participate in the lottery. Therefore, our results for middle and high school cannot be generalized to all families in the city.[5] Second, the study assumes that residential location is exogenous. That is, a family decides where to live and then ranks schools, rather than the other way around. Hastings et al. (2005) noted the possibility that endogenous residential location could lead to overestimating the importance of distance. If families move closer to schools they prefer, the observed relationship between distance and school choice may in fact be masking a preference for specific school attributes. They addressed this by taking advantage of a policy that abruptly changed

[4] A more practical way to replicate successful programs would be to replicate the model in different campus locations. These replications can also be simulated, but we chose to hold distance and neighborhood characteristics constant.

[5] We estimated preferences separately for those entering pre-K, for which lottery participation was mandatory and universal, and those entering kindergarten, where lottery participation was optional, and the parameter estimates were nearly the same.

neighborhood school boundaries, likely producing exogenous variation in the default school. Harris and Larsen note that in a pure choice system like that of New Orleans, where there are no by-right schools, the housing decision does not carry option value for a neighborhood school, so locating near a school is only necessary for reducing commute time. They also note other features of the choice process that likely mitigate concerns about endogeneity, such as the effect of parental preference for short commutes to work, complexity of the combinations of school characteristics, and the uncertainty, presumably of parents at the time of their residential location decisions, about where schools will locate. We explore the endogeneity of location by exploiting the depth of school rankings. Specifically, we test the sensitivity of our results by the rankings depth of choices. Under the assumption that choosers move to be near a top choice, the ordering of their lower-ranked alternatives cannot be as easily gamed and therefore are more likely to represent true preferences over attributes.

Third, there are important omitted variables. Most notably, we did not have measures of the applicants' academic ability, so we could not model that aspect of heterogeneity. That would limit our ability to gauge whether school choice might lead to stratification by ability, other than through income or race. Fourth, we assume that choosers honestly rank their preferences. We discuss this assumption later in the paper, but the basic justification is that the assignment algorithm is strategy proof and was conveyed as such through extensive outreach to families who were using the common school-choice application. In the remainder of the paper, we describe the data and methods, empirical findings, simulation results, and conclusions.

II. CONTEXT, DATA, AND METHODS

Washington D.C. unified school choice lottery

To understand the data for this study, it helps to know about school choice in Washington, DC and the process that generated the parent rankings of schools. The public charter-school sector in DC has grown rapidly since its beginning in 1996, with particularly rapid growth occurring in the early 2000s, both in number and popularity of schools. Historically, charter schools with demand that exceeds capacity have held their own lotteries for admitting students. In 2014, DC centralized school admissions by implementing a common application and lottery system for nearly all public schools (both traditional district schools and nearly all charter schools), known as My School DC. The traditional public school system, the DC Public Schools (DCPS), sets aside seats for parents who wish to apply from outside their neighborhood boundaries. Under the new system, any family wishing to send their child to a school other than their by-right school (neighborhood school or school they currently attend) must submit a common application, ranking up to 12 of their most preferred schools from a list of all district and charter schools offering the relevant grade. Spaces available to lottery applicants in each participating school and grade level are then matched to students using a random assignment mechanism.

The student-school matching process uses a deferred acceptance algorithm (Roth 2008; Abdulkadiroglu, Pathak, and Roth 2009). Under this algorithm, each applicant is randomly assigned one unique number that determines the queue orderings among each group of students applying to the same school and grade level. When the number of applications to a school and grade exceeds capacity, the algorithm allocates available spaces according to this randomly generated queue ordering. Each student is then temporarily matched to their highest ranked school for which space was allocated to them, while any spaces allocated to the student in less preferred schools is then made available to other students. The algorithm repeats this process, attempting to match each student to his or her highest ranked school until no further improvements to match rankings are possible. For schools ranked as more preferred than the school the student is ultimately matched to, the student is assigned a waitlist position according to his or her queue position among all other applicants to that school who were not matched to a more preferred option. These waitlist positions are sequentially converted to matches when other students decline enrollment in their matched school.

Some schools participating in the Washington D.C. unified school-choice lottery also add priority factors. These include whether the student is (1) currently attending another campus of the charter school for which the student is applying, (2) has a sibling currently enrolled at the selected school, or (3) has a sibling that was matched to the same school but is in a different grade. Additionally, some DC public high schools are specialized high schools that assign students a queue position according to academic merit. Within schools that honor these additional priorities, the lottery assigns applicants within their relevant priority status group before using the lottery mechanism to determine the relative queue positions of students within each status group.

Importantly, the algorithm used by the common lottery is designed to be strategy proof, which means it disincentivizes any ranking of school choices other than by the applicant's true valuations for each ranked school. This is because (1) the matching method does not prioritize applicants for a given school based on the applicant's ranking of that school, and (2) the lottery-assigned priority by which students are matched to available spaces does not depend on or vary across the set of schools chosen. Instead, the algorithm will always produce matches at the student's highest-ranked school for which there is capacity, after accommodating students randomly assigned a higher match priority. Therefore, any rankings of school choices that deviate from an applicant's true preferences have the potential to result in a less-preferred match and, in the most favored scenario, will result in a match of equal preference. Because our analyses rely on applicant rankings of schools reflecting true preferences, more important than the strategy-proof properties of the algorithm is that applicants perceive it to be strategy proof and behave accordingly. Indeed, My School DC used consistent messaging to parents, which not only specified that schools should be ranked according to their true preferences for enrollment, but also conveyed the strategy-proof design of the algorithm, and specifically explained that the likelihood of being matched to a preferred school did not depend on its ranking on the application.

Data sources

We combine data from several sources to analyze parental preferences for schools in Washington, D.C. Applicants' rank-ordered school choices come from applications submitted for the 2014 DC common lottery. We match applicants to enrollment records from SY 2013–2014 (during which time applications were submitted) and SY 2014–2015. The combination of applications and enrollment data also allows us to identify the set of DCPS and charter school options available to students outside the lottery process. This set of additional school options includes "in-boundary" schools, which students are eligible to attend based on each applicant's address of residence; currently attended schools, which students may return to the following year; and "feeder" schools, to which students can matriculate from the school they currently attend. The matched enrollment data also provide characteristics of applicants, including students' gender, ethnicity, English learner status, special education status, and two proxies for income status; free or reduced-price lunch (FRL) eligibility, which is based on family income being below 130 percent of the poverty line; and direct certification for free meals, which indicates the student is homeless, served by the district's foster care program, or qualifies for the public assistance programs.[6]

To analyze preferences for schools as a function of school-level (and school-grade-level) attributes, we bring in data from multiple sources which were observable by parents at the time of application. These are (1) information from school profiles displayed on the My School DC website during the application period, including school size, availability of nearby public transportation lines, math and reading proficiency levels, racial composition of students, and before- and after-school child care services, (2) additional school-level information from the 2013 DC equity reports, which are school profiles released by the state education agency and include measures of gains in student proficiency levels and achievement-related accountability measures, and (3) annual data on reported crimes near school locations that were calculated by the research team. Except for reported crimes, the information captured by these data were available to families as they shopped for schools. The My School DC web portal linked to a school profile website that allowed parents to see snapshot information as well as a linked website called Learn DC that provided more detailed school profiles. The variables we used from these data sources are described in more detail in the findings section.

Finally, some additional pieces of data are brought in to capture applicant-specific attributes of schools. Using school addresses of applicants and schools, we account for distance in four different ways: straight-line distance, right-angle distance, shortest driving distance using the fastest route according to a popular navigation service, and commuting time using the same route and navigation service. We also created the percentage of each school's student body sharing certain characteristics of each applicant, including ethnicity, FRL eligibility, direct certification status, and English learner status.

We also use Census block group level data from the American Community Survey (ACS) to supplement information on both neighborhoods in which the schools are located and the neighborhoods in which the applicants are located. Census block groups contain between approximately 600 and 3,000 individuals, so these variables capture the income, education, race, and ethnicity of the immediate area around each school and each applicant.[7]

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[6] The public assistance programs captured by direct certification status are the Supplemental Nutrition Assistance Program (SNAP), or food stamps, and Temporary Assistance for Needy Families (TANF). Direct certification is preferred to FRL because DCPS had begun adopting community eligibility for free lunch, which means that eligibility status was conferred automatically on certain families, even if they did not qualify based on income, if they were attending schools with a concentration of otherwise-eligible families.

[7] The ACS variables describing characteristics of individuals and households within a Census block group are weighted estimates from five years of annual ACS survey data.

Descriptive statistics

We focus our analysis on the entry grade levels, specifically students applying for pre-kindergarten or kindergarten to enter elementary schools, grades 5 or 6 to enter middle schools, or grade 9 to enter high school, which are the most common grade levels for which families submitted applications.[8] Because preferences for school attributes likely differ by grade level—before-school care programs may be more desirable for young children than secondary students—we conduct our analyses separate for elementary, middle, and high school entry grades. In Table 1, we present the unique number of schools in the choice set for applicants in each of these grade ranges, as well as the unique number of school choices across all grade levels. Over all grade levels, charter schools make up roughly 45 percent of the school-choice options available through the lottery. This excludes 11 charter schools that opted out of the common lottery assignment system (of 102 charter schools in total) and held their own admissions processes in the first year.

Table 1. Number of schools by sector and entry grade

Sector	Elementary: Pre-K and kindergarten	Middle school: Grades 5 and 6	High school: Grade 9	Any grade level
Pubic charter schools	54	42	17	91
DCPS	82	92	15	110
Total	**136**	**134**	**32**	**201**

Note: Schools may serve grade levels in more than one category.

The number of choices available at the high school level is smaller because high school students in DC, as in most school districts around the country, are concentrated in a smaller number of larger buildings than are younger students. In our data, there were 32 high schools available to rank, nearly evenly split between the charter and traditional school sector. Additionally, of the 15 participating DCPS high schools, 6 are selective programs that give preference in the selection process based on merit in the same way that an applicant with an enrolled sibling would have preference. Selective admission among these schools could have deterred some applicants with a low likelihood of admission from ranking such schools, but we suspect that the schools are omitted from the rank-ordered list, instead of being ranked lower than a less preferred school. Therefore, it is reasonable to interpret the ordering within the ranked alternatives, even for high school applicants, as a meaningful revelation of preferences.

We restrict our estimation sample to include all lottery applicants with a valid DC address—roughly 98 percent of all submitted applications—to ensure that we observe the distances between chosen schools and the applicant's residence. As shown in Table 2, our sample includes 10,600, 2,389, and 3,036 unique applicants in elementary, middle, and high school entry grades, respectively. The dramatically larger number of applicants for elementary entry grades is explained by the fact that DC public schools do not have any right-to-attend options for pre-

[8] We obtained data for all choosers, including those applying to non-entry grades, but do not present findings for those students in this paper. Entry grades, as we have defined them, accounted for 72 percent of all applications. Non-entry grade applicants are likely to have different motivations and circumstances than entry-grade applicants.

kindergarten grade levels. Therefore, all DC residents hoping to enroll their pre-kindergartners in a DC public school or charter school must apply for admission through the school-choice lottery.

Table 2. Applicant characteristics by entry grade

	Elementary: Pre-K and kindergarten	Middle school: Grades 5 and 6	High school: Grade 9	All grade levels
Female	0.50 (0.50)	0.50 (0.50)	0.53 (0.50)	0.51 (0.50)
Race/ethnicity				
Asian	0.02 (0.11)	0.02 (0.13)	0.02 (0.12)	0.01 (0.10)
African American	0.65 (0.45)	0.72 (0.44)	0.75 (0.42)	0.71 (0.43)
Hispanic	0.14 (0.31)	0.14 (0.34)	0.16 (0.35)	0.14 (0.32)
White	0.16 (0.34)	0.10 (0.29)	0.06 (0.23)	0.11 (0.29)
Multiple/Other	0.03 (0.16)	0.02 (0.14)	0.02 (0.11)	0.03 (0.14)
Free or reduced-price lunch	0.49 (0.29)	0.53 (0.50)	0.54 (0.47)	0.53 (0.39)
Direct certified	0.36 (0.45)	0.42 (0.49)	0.39 (0.48)	0.39 (0.46)
Limited English proficient	0.11 (0.29)	0.05 (0.22)	0.07 (0.25)	0.09 (0.27)
Special education status	0.06 (0.20)	0.13 (0.33)	0.13 (0.33)	0.10 (0.28)
Number of Applicants	**10,600**	**2,389**	**3,036**	**22,368**

Note: Cell values are subsample means with standard deviations in parentheses. The fourth column includes all applicants applying for grade levels Pre-K3 through grade 12.

The mean applicant characteristics presented in Table 2 show little variation across grade levels in the composition of applicants, save for slightly higher and lower percentages of white and African American applicants, respectively, at the elementary level.

Along observable characteristics, the pool of lottery applicants is fairly representative of the population of public school students in the city.[9] In Table 3, we compare the composition of 2014 lottery applicants for all grades (pre-K through grade 12) with that of students concurrently enrolled in all DCPS or charter schools during the application and lottery process. Although

[9] We observe some characteristics of applicants only within the enrollment data and therefore are unable to determine these characteristics for students who were both (1) not enrolled in a DCPS or charter school in the school year during the application process and (2) did not enroll in any DCPS or charter school in the subsequent year. For characteristics used in the analyses, we impute values for this group of students based on characteristics of the neighborhood (Census block group) in which they live using the ACS data.

differences between these groups are statistically significant for several characteristics, most of these differences are not substantively meaningful. None is greater than 3 percentage points.

Table 3. Comparison of lottery participants to all enrollees

	Lottery applicants	Enrolled students	Difference (applicants – enrollees)
Female	0.51 (0.50)	0.50 (0.50)	0.01
Race/Ethnicity			
Asian	0.01 (0.10)	0.02 (0.12)	-0.00*
African American	0.71 (0.43)	0.73 (0.44)	-0.02**
Hispanic	0.14 (0.32)	0.14 (0.35)	-0.01*
White	0.11 (0.29)	0.09 (0.29)	0.02**
Multiple/Other	0.03 (0.14)	0.02 (0.13)	0.01**
Free or reduced-price lunch	0.53 (0.39)	0.55 (0.50)	-0.02**
Direct certified	0.39 (0.46)	0.42 (0.49)	-0.03**
Limited English proficient	0.09 (0.27)	0.09 (0.29)	-0.00
Special education status	0.10 (0.28)	0.13 (0.34)	-0.03**
Number of students	**22,368**	**76,296**	

Note: * $p < .05$, ** $p < .01$, *** $p < .001$
Numbers in columns 1 and 2 are means for each student indicator with standard deviations in parentheses.

Model and estimation strategy

Our estimation strategy employs a discrete choice framework and investigates parental preferences for school characteristics using a rank-ordered logit model (Beggs, Cardell, and Hausman 1981), sometimes referred to as an exploded-choice logit (Punj and Staelin 1978; Chapman and Staelin 1982). We begin by considering an applicant's choice of school as a utility maximizing decision. In particular, we assume applicants' valuations of schools are a function of observable characteristics of the school, which include characteristics that do and do not differ between applicants of the same school, and other unobservable factors, which we treat as random. An applicant's utility derived from a particular school is defined as

$$(1) \quad U_{ij} = X_j^{'}\beta + Z_{ij}^{'}\gamma + \varepsilon_{ij}$$

where *i* and *j* index individual applicants and schools, respectively. X_j is a vector of observable attributes of school *j,* including measures of schoolwide academic performance and school neighborhood demographics. Attributes of each school that vary by applicant, such as the proximity of the applicant household to the school, are captured by the vector Z_{ij}. ε_{ij} is an idiosyncratic term determined by unobserved factors of applicant *i*'s preferences for school *j.* The probability that applicant *i* values school *j* above all other $J-1$ school choices then depends on the distribution of ε_{ij}. Assuming an independent type-I extreme value distribution leads to the typical logit model expression for this probability:

$$(2) \quad \Pr\left[U_{ij} > U_{ik}, \forall k \neq j\right] = \frac{e^{X_j'\beta + Z_{ij}'\gamma}}{\sum_{k=1}^{J} e^{X_j'\beta + Z_{ij}'\gamma}}$$

Because we observe the ordered rankings of multiple schools by applicants, we can use applications from the unified lottery to infer each applicant's ordinal preferences among all ranked schools. Using this larger set of information shifts our focus to the probability of applicants possessing a particular rank ordering of valuations among school choices, which is simply the joint probability of a series of sequential choices. For example, given a rank ordering where *J* school choices are indexed according to the strict preference ranking of the applicant, this probability is simply the joint probability of (1) school 1 being preferred to all schools, (2) school 2 being preferred to all schools that are not school 1, (3) school 3 being preferred among all schools that are not school 1 or 2, and so on. That is,

$$(3) \qquad \mathsf{L}_i = \Pr\left[U_{i,j=1} > U_{ij=2} > \cdots > U_{i,j=J} \middle| \beta, \gamma\right] = \prod_{j=1}^{J=1} \frac{e^{X_j'\beta + Z_{ij}'\gamma}}{\sum_{k=1}^{J} \delta_{ijk} e^{X_k'\beta + Z_{ik}'\gamma}}$$

where $\delta_{ijk} = 1$ if $U_{ij} > U_{ik}$ and 0 otherwise. This joint probability leads to the log likelihood function expressed in equation (4), where *N* is the number of independent applicants and J_i denotes that the number of ranked school-choice alternatives can vary by applicant.

$$(4) \quad \log \mathsf{L} = \sum_{i=1}^{N} \sum_{j=1}^{J_i} X_j'\beta + Z_{ij}'\gamma + \sum_{i=1}^{N} \sum_{j=1}^{J_i} \log\left[\sum_{k=1}^{J_i} \delta_{ijk} e^{X_k'\beta + Z_{ik}'\gamma}\right]$$

Under this setup, we obtain maximum likelihood estimates of the choice parameters β and γ. In Section III, we give estimation results.

Explanatory variables

We estimated a rank-ordered logit model that tested five domains of school-choice factors: convenience, school demographics, school neighborhood, school academic indicators, and other school offerings. There are many different ways to measure these factors and to specify their relationship with consumer rankings. We estimated a benchmark model that represents the most defensible functional form and choice of measures, but tested the robustness of this model by varying the measures, scaling, and specifications one at a time and re-estimating the logit.

Benchmark results are presented and discussed first, followed by a summary of the sensitivity analysis.

Convenience is measured by commute distance from home to each school alternative, where commute distance is computed as right-angle distance.[10] We also tried a variety of alternative measures of commuting distance and time and found that the results were not sensitive to the choice of a particular distance metric. This domain also includes indicators for whether the school was near a subway stop or whether it was on two or more bus lines (to differentiate major from minor bus routes).

School demographics include the percentage of students in a school who are of the same race/ethnic group as the chooser. We estimate a quadratic relationship between the percentage of same-race students and school rankings. We later investigate heterogeneous preferences for the racial composition of a school's student body and allow the own-race coefficients to vary by race/ethnicity of the chooser. The other school demographics variable is the percentage of students who are low income, as measured by direct certification for public assistance.[11] All percentages are divided by 10 so the coefficients can be more easily interpreted as the change in utility associated with an increase of 10 percentage points.

Several **academic indicators** were available as public information to parents choosing schools, some of which were more readily accessible than others. The most accessible one is the school's proficiency rate in the prior year, which was prominently displayed on each school's profile page on the My School DC website during the lottery application period. Other academic indicators were accessible through external sources, such as the annual DC equity reports, some of which were linked from the My School DC school profile pages. One such indicator is the school's median growth percentile score from the prior year, which we refer to as the growth score.[12] This score is meant to account for students' prior achievement. We re-scaled proficiency rates and growth scores, like percentages, to range from 0 to 10, so that coefficients can be interpreted as the effects of a 10-point increase. In addition to the academic proficiency and growth indicators, we note that DC has two accountability systems that produce categorical ratings. One pertains just to charter schools and has three tiers: a top, middle, and bottom tier, labeled 1, 2, and 3, respectively. Charter schools are known to advertise their status if they are Tier 1 schools. The other accountability rating is for all schools in the city—district and charter—and has four levels, in order from lowest to highest score on a continuous accountability rating: priority, developing, rising, and reward. A fifth category, called focus, is

[10] Right angle distance is the absolute value of the difference between school and home x coordinates plus the absolute value of the difference between school and home y coordinates. It assumes that travel occurs along a grid that only has east-west and north-south roads.

[11] We also estimated models using FRL eligibility as the poverty measure, but this metric has become less accurate over time in DC. In recent years, schools and families in DC have faced weaker incentives to document eligibility and designate a student as FRL because of "community eligibility," which designates everyone in certain schools as eligible for free meals if a sufficient percentage of students in that school are eligible.

[12] The median growth percentile is explained to parents as "a model that measures academic growth by comparing groups of students with similar test-score history." It is calculated using a statistical model of student progress over previous years on the DC Comprehensive Assessment System (DC CAS) assessments, sometimes referred to as the Colorado Growth Model (Betebenner 2007; Walsh and Isenberg 2013).

assigned to schools that have large achievement gaps between subgroups of students and is typically considered a low rating similar to priority.

School neighborhood characteristics include the crime rates, measured as the average number of violent crimes per month reported within 500 feet of the school's address over a two-year period. The same measure is used for property crimes.[13] As alternatives, we also calculated crime rates using larger radii of 1,000 and 1,500 feet from the school, as well as defining the area over which we calculated per-capita crime rates for each school as its Census tract and block group. Other school neighborhood variables are drawn from the American Community Survey and include several measures of SES of residents of the Census block group in which the school is located. In the benchmark model, we included the log of the median household income in the school's Census block group. Alternative specifications add more variables, such as the prevailing education levels in the Census block group, race/ethnicity, poverty, welfare receipt, and other demographics. Many of these variables were correlated with each other, so we relied on a more parsimonious specification for the benchmark model.

School neighborhood characteristics are included in the model primarily as control variables, but it is important to note that policymakers have considerable control over these factors through site approvals, disposal of "surplus" city buildings that can be used for charter schools, and selective school closures. The neighborhoods in which most charter schools and many DCPS schools are found result from decisions by the council and mayor of DC as well as the District's Public Charter School Board.

Finally, the **other school offerings** include average class size (number of students per core class), an indicator for whether the school requires students to wear a uniform, availability of before-school care, and availability of after-school care. All of these variables are defined for DCPS schools only, not for charter schools.[14] For charter schools, the values of each amenity variable is set to zero and a sector dummy is included. Other dummies are also included in the model, but not reported here because they do not have a useful policy interpretation. They include indicators for missing values that have been imputed and a dummy for whether the applicant has a sibling enrolled in the school.

III. FINDINGS

Main findings

The logit results are consistent with findings in the literature we summarized earlier. These results suggest that convenience, school academic performance, and student body composition are predictive of how parents rank school alternatives. The results in Table 4, showing separate models by entry grade, indicate that choosers were significantly more likely to rank schools higher if the schools were closer to home, on bus or subway lines, had a higher percentage of students from their own race/ethnic group, and had higher test score proficiency rates.

[13] Violent and property crimes are those defined by the FBI's Uniform Crime Reports.

[14] The information was added for all schools in later years.

Table 4. Rank-ordered logit results, benchmark model

School characteristics	Applicants entering… Elementary school		Middle school		High school	
CONVENIENCE						
Distance (miles)	-0.094	***	-0.057	***	-0.021	**
On at least two bus lines	0.098	***	0.225	***	0.043	
On subway	0.113	***	0.063		0.136	*
SCHOOL DEMOGRAPHICS						
Own-race percentage/10	0.061	***	0.163	***	0.172	***
Own-race percentage/10 squared	-0.002		-0.016	***	-0.001	**
Percentage low income (direct-certified)/10	-0.161	***	0.149	***	0.038	
ACADEMICS—PROFICIENCY AND GROWTH						
Proficiency rate/10	0.085	***	0.070	**	0.143	***
Median growth percentile/10 (math)	-0.008		-0.111	***	-0.196	***
ACADEMICS—CHARTER SCHOOL ACCOUNTABILITY RATING						
PMF Tier 1 (charters only)	0.101		0.228		-0.292	*
PMF Tier 2 (charters only)	-0.003		0.028		-0.019	
PMF Tier 3 (charter only) - omitted category	--0--		--0--		--0--	
ACADEMICS—STATE ACCOUNTABILITY RATING						
1. Reward	0.061		0.383	**	1.204	***
2. Rising	-0.028		0.121		0.541	***
3. Developing	0.011		0.138		0.296	*
4. Priority - omitted category	--0--		--0--		--0--	
Focus school: Subgroup gaps	0.007		-0.262	*	0.114	
Sample size (student-school combinations)	**51,572**		**9,045**		**11,543**	

Notes: * $p < .05$, ** $p < .01$, *** $p < .001$; --0-- parameter is constrained to zero.

Variables with "/10" can be interpreted as one unit representing 10 percentage points.

PMF is "Performance Management Framework," which is used to rate charter schools.

Sample for each column is applicants to entry grades for the respective school level: Pre-K and kindergarten for elementary, grades 5 and 6 for middle school, and grade 9 for high school.

There is evidence at the middle and high school level that own-race preferences are non-linear, on average. Specifically, choosers were more likely to rank a school higher if their own child's race/ethnic group was better represented in the school, but that increase in likelihood of ranking the school higher was largest when the own-race/ethnicity percentage was relatively low. As the own-race/ethnicity percentage rises, the relationship is weaker and even negative, suggesting a taste for diversity.

The logit coefficients reported in the table are not literally the effect on school ranking probabilities. They represent the effect of each variable on utility in our model, but higher utility translates to a greater probability of being ranked higher, so the discussion here focuses primarily on sign and statistical significance of the coefficients. Standard errors are reported separately in supplemental tables (Appendix C).

Although we focus on the sign and significance of the parameter estimates, a helpful way to interpret the magnitude of the logit coefficients is to convert them to odds ratios, which express the relative odds of ranking the school higher than an alternative. In Table 5, we present some illustrative contrasts between pairs of middle schools that are identical in every way except for a change in one attribute. The distance coefficient of -0.057 implies an odds ratio of 0.94, which means that for every additional mile of commute distance to a school, the relative odds of ranking it above the alternative fall by 6 percent. This can be translated further into a probability of choosing the school that was one mile farther over an otherwise identical school, which would fall from 50 percent (indifferent between the two) to 48.6 percent, a decline of about 1.4 percent. The own-race coefficients (on the linear and squared term) suggest that an increase in the percentage of students in the school whose race/ethnicity is the same as the applicant's from 10 to 20 percentage points is associated with an odds ratio of 1.12 for middle school choosers, while a contrast between 40 and 50 percentage points is associated with a smaller odds ratio of 1.02. For a 10-point increase in the percentage of students who are proficient on the state standardized test, the odds ratio is 1.07. For a charter school being in Tier 1 versus Tier 3, the odds ratio is 1.26, making the predicted probability of selecting it over an identical alternative 56 percent.

Table 5. Magnitude of the logit coefficient estimates

Explanatory variable	Logit coefficient *β*	Odds ratio (OR) *exp(β*ΔX)*	Change in probability of choosing over otherwise identical school *OR/(1+OR) – 0.50*	Distance between two schools to make chooser indifferent *β/β(distance)*
Distance: One-mile increase	-0.057	0.94	-0.014	1.00 mile
Own race/ethnicity	0.163			
Own race/ethnicity squared	-0.016			
Increase from 10 to 20 percent		1.12	0.029	2.07 miles
Increase from 40 to 50 percent		1.02	0.005	0.36 miles
Proficiency rate: 10-point increase	0.070	1.07	0.017	1.23 miles
Tier 1 versus Tier 3 on PMF	0.228	1.26	0.057	3.86 miles

Notes: Logit coefficients are from Table 4, middle school model.
PMF is "Performance Management Framework," which is used to rate charter schools.

Yet another way to interpret the magnitudes of the coefficients is to express them in distance units. This is done by dividing any given coefficient by the coefficient on distance. For example, the model results suggest that parents would be willing have their children commute an additional 1.23 miles to a middle school that has a 10-point higher proficiency rate on state standardized tests.

The benchmark model findings were almost all consistent across choosers applying to the entry grades for elementary school (pre-kindergarten or kindergarten), middle school (applying to grades 5 or 6), and high school (applying to grade 9). However, there were some differences in magnitude of effects, and within the domain of academic performance the specific indicator that was statistically significant varied by grade span. Although proficiency rate—the percentage of students scoring above a predetermined cut point on the state standardized test—was positively related to school preference for applicants of all grade spans, the categorical state accountability ratings were progressively more important for applicants of later grade levels. For applicants to elementary schools, the coefficients for these categories were not statistically significant. For applicants to middle school, the coefficient for the top accountability category was positive and significant, while each of the coefficients for the three highest categories were larger still among high school applicants.

The coefficient on the growth measure was negative and significant for both middle and high school applicants. One possible explanation for this is that with prior-year (2013) proficiency rate included in the model, growth is likely to capture lagged proficiency (2012) with the sign reversed. In other words, controlling for proficiency, schools with high growth are likely to be those that had lower proficiency in 2012. We did not include 2012 proficiency in the benchmark model because of collinearity with 2013 proficiency rates, but when we included it in an alternative model, the coefficient on school growth measures reversed sign for high school choosers. For middle school choosers, it did not change much at all, so this explanation did not consistently account for the observed findings.

We also examined preferences for school neighborhood characteristics, such as crime rates and median income, as well as amenities like class size and school uniform policies. Preferences for school neighborhood characteristics, which are presented in Appendix A because they were not our main focus, did not uniformly support the hypothesis that schools in higher SES neighborhoods would be ranked higher. This general conclusion was unchanged when we added more variables to the model from a rich source of Census data or when we measured those variables relative to the neighborhood of the chooser. We added variables for the inequality in the neighborhood (measured by a Gini coefficient for household incomes), the percentage of residents with at least a college degree, the percentage of African American residents, the percentage of school-age children in poverty, and the percentage of children in households receiving public assistance.[15] Findings on crime in particular were counter-intuitive, suggesting that schools were more likely to be ranked higher if they had less reported property crime, but more reported violent crime. We examined these findings in detail and explored their robustness. The full set of findings is reported in Appendix A. The findings for school amenities were puzzling as well. In particular, there was a statistically significant positive coefficient on class size, suggesting that schools with larger classes were more likely to be ranked higher. We discuss this result and its robustness in Appendix A as well.

Subgroup analysis: Preferences by income and race

We model heterogeneity in consumer preferences in two ways. First, we estimate separate parameters for subgroups by interacting chooser characteristics with explanatory variables in the model. Second, we allow the coefficients to be random and estimate the moments of their distributions using a mixed logit model, discussed below in the sensitivity analysis.

[15] In the past 12 months, pertains to Supplemental Security Income, Public Assistance income, or SNAP.

Income

We first interacted all of the model parameters with an indicator for low-income chooser. Whether we used direct certification for FRL meal eligibility or students' individual FRL eligibility status did not result in substantively different conclusions. We found that the economic status of the choosers made a difference in preferences at the elementary and middle school levels, but not at the high school level. We summarize the results in Table 6. Among applicants to elementary schools, low-income choosers differed most from other choosers in terms of their preferences about school demographics. Notably, lower-income choosers did not share the preference for schools with higher percentages of students of the same race/ethnicity and lower percentages of low-income students as higher income choosers. Also their distance preference was weaker by a statistically significant margin.

For applicants to middle school, the most interesting difference for low-income choosers is that, although their rankings were also influenced by school academic performance measures, the effect operated through the school's proficiency rate and not the accountability categories. For higher-income choosers, however, proficiency rates were not associated with school-choice rankings. Rather, their rankings were more influenced by the accountability categories and not the proficiency rate.

These results have interesting implications for how parents find and evaluate information on the academic quality of schools. Applicants for elementary school entry grades (pre-K and kindergarten) and lower-income middle school applicants more often ranked schools higher based on proficiency rates—information that was directly observable on the My School DC lottery application website. Middle school applicants with higher income, and high school applicants in general, more often ranked schools higher based on accountability ratings—information that was not immediately available on the application portal and required more effort to find.

Table 6. Interactions with low-income status

School Characteristics	Elementary school		Middle school		High school	
	Main effect	Interaction	Main effect	Interaction	Main effect	Interaction
CONVENIENCE						
Distance (miles)	-0.107***	0.037***	-0.042***	-0.032	-0.014	-0.017
On at least two bus lines	0.083***	0.038	0.298***	-0.179	0.073	-0.084
On subway	0.132***	-0.019	0.020	0.080	0.173*	-0.113
SCHOOL DEMOGRAPHICS						
Own-race percentage/10	0.070***	-0.059*	0.189***	-0.064	0.142**	0.117
Own-race percentage/10 squared	-0.002	0.003	-0.019***	0.007	-0.007	-0.011
Percentage low income (direct-certified)/10	-0.218***	0.190***	0.159***	0.001	0.033	0.045
ACADEMICS—PROFICIENCY AND GROWTH						
Proficiency rate/10	0.088***	-0.007	0.029	0.107*	0.130***	0.039
Median growth percentile/10 (math)	-0.007	-0.006	-0.091***	-0.026	-0.189***	-0.011
ACADEMICS—CHARTER ACCOUNTABILITY RATING						
PMF Tier 1 (charters only)	0.105	-0.015	0.378	-0.305	-0.168	-0.316
PMF Tier 2 (charters only)	-0.005	-0.031	0.131	-0.148	0.001	-0.011
PMF Tier 3 (charters only) - omitted category	--0--		--0--		--0--	
ACADEMICS—STATE ACCOUNTABILITY RATING						
1. Reward	0.066	0.027	0.811***	-0.920***	1.405***	-0.431
2. Rising	-0.004	-0.017	0.378*	-0.511*	0.708***	-0.322
3. Developing	-0.003	0.038	0.235	-0.233	0.600***	-0.580*
4. Priority - omitted category	--0--		--0--		--0--	
Focus school: Subgroup gaps	0.064	-0.109	-0.130	-0.221	0.219	-0.152
Sample size (student-school combinations)	**51,572**		**9,045**		**11,543**	

Notes: * $p < .05$, ** $p < .01$, *** $p < .001$, --0-- no p-value, parameter is constrained to zero.

For each school level, main effect and interaction columns report coefficient estimates from the same regression. Coefficients reported in the interacted columns are those for the listed school characteristic interacted with the student's direct certification status for free school meals. Because the coefficients reported in the main effects columns correspond to the overall association among all students, the sum of the main and interacted coefficients should be interpreted as the association between school characteristics and preferences for schools for direct-certified students.

PMF is "Performance Management Framework," which is used to rate charter schools. Sample for each column is applicants to entry grades for the respective school level: Pre-K and kindergarten for elementary, grades 5 and 6 for middle school, and grade 9 for high school.

Model includes school neighborhood and other school attributes, but coefficients not shown.

Entry grades are pre-K and kindergarten for elementary, grades 5 and 6 for middle school, and grade 9 for high school.

Table 7. Separate model parameters by race/ethnicity

School Characteristics	Elementary			Middle School			High School		
	African American	White	Hispanic	African American	White	Hispanic	African American	White	Hispanic
CONVENIENCE									
Distance (miles)	-0.075***	-0.208***	-0.079***	-0.064***	-0.017	-0.047	-0.022**	-0.004	-0.031
On at least two bus lines	0.086***	0.039	-0.031	0.165**	1.610***	0.006	0.005	-0.931	0.345
On subway	0.121***	0.148***	0.220***	0.016	0.310	0.235	0.136	1.834*	0.233
SCHOOL DEMOGRAPHICS									
Own-race percentage/10	-0.013	0.109***	0.047	0.188***	0.178	0.040	0.294	-0.169	0.485*
Own-race percentage/10 squared	0.001	-0.009*	0.003	-0.020***	-0.034	-0.004	-0.019	0.003	-0.064*
Percentage low income (direct-certified)/10	-0.062***	-0.438***	-0.161***	0.214***	-0.110	-0.037	0.072	-0.033	0.182
ACADEMICS—PROFICIENCY AND GROWTH									
Proficiency rate/10	0.095***	0.106***	0.057*	0.089**	0.144	-0.053	0.150***	-0.215	0.192*
Median growth percentile/10 (math)	-0.022**	0.016	-0.021	-0.093***	-0.251***	-0.125*	-0.222***	-0.248	-0.203**
ACADEMICS—CHARTER ACCOUNTABILITY RATING									
PMF Tier 1 (charters only)	-0.009	0.190	0.345*	0.184	2.122***	0.598	-0.333*	-0.438	-0.044
PMF Tier 2 (charters only)	-0.039	-0.039	0.056	-0.053	0.538	0.644	-0.125	-1.669	0.222
PMF Tier 3 (charters only) - omitted category	--0--	--0--	--0--	--0--	--0--	--0--	--0--	--0--	--0--
ACADEMICS—STATE ACCOUNTABILITY RATING									
1. Reward	0.024	0.021	0.311	0.340*	-0.066	0.627	1.263***	5.257*	1.416*
2. Rising	-0.067	0.050	0.188	0.128	-0.213	0.385	0.589***	3.338*	0.882
3. Developing	-0.010	-0.266	0.434*	0.134	0.908	0.001	0.270	1.611	1.198*
4. Priority - omitted category	--0--	--0--	--0--	--0--	--0--	--0--	--0--	--0--	--0--
Focus school: Subgroup gaps	-0.034	0.158	0.331*	-0.211	0.258	-0.104	0.230	1.316	0.331
Sample size (student-school combinations)		**51,572**			**9,045**			**11,543**	

Notes: * $p < .05$, ** $p < .01$, *** $p < .001$; --0-- no *p*-value, parameter is constrained to zero.

PMF is “Performance Management Framework,” which is used to rate charter schools. Sample for each column is applicants to entry grades for the respective school level who identify as the corresponding race category.

Model includes school neighborhood and other school attributes, dummies for missing values, but coefficients not shown. See Appendix A for detailed set of covariates.

Entry grades are pre-K and kindergarten for elementary, grades 5 and 6 for middle school, and grade 9 for high school.

Race/ethnicity

We also estimated interactions with each of the three largest race/ethnicity groups, as shown in Table 7. Those groups are white choosers, Hispanic choosers, and African American choosers.[16] We found differences among choosers' race/ethnic groups in their own-group preferences and the nature of those differences varied, depending on the grade span to which the choosers were applying (elementary, middle, or high school). For each entry grade, the joint hypothesis test of whether the coefficients for African American choosers differed from those of each of the other two groups was easily rejected, meaning that differences were significant overall. Many of these preference parameters by race/ethnicity subgroup are no longer statistically significant once we disaggregate. Nevertheless, we present the results from Table 7 in graphical form in Figure 1, as exploratory findings which may provide clues about race preferences that should be explored in greater depth in contexts where there is more overlap in racial composition of the school alternatives.

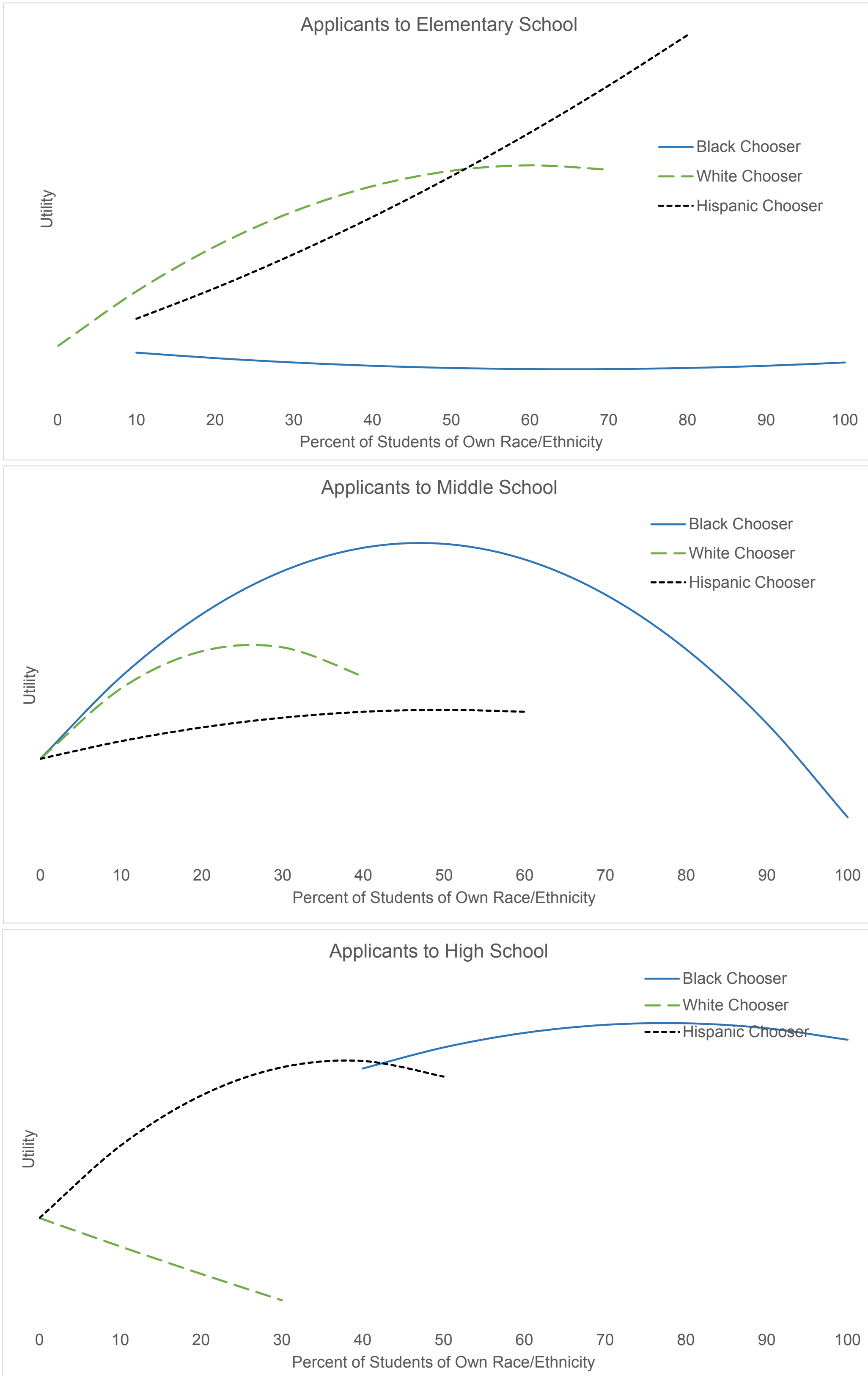
In DC, there were large differences in the range of own-race variation each group faced. African American choosers were typically deciding between schools where they might be in a majority versus a super majority, whereas white and Hispanic choosers were typically deciding between schools where they would be in a small minority versus a larger minority.

For those applying to enter elementary school, white choosers tended to prefer schools with greater percentages of students who were from their same race/ethnic group. Also, for white choosers, the preference was strongest for schools where their children would be in a small majority (up to 60 percent), with a slight decline in this preference among the few schools with a higher proportion of white students, as evidenced by the curvature of the relationship between own-group percentage and utility shown in the top panel of Figure 1. For Hispanic choosers, the relationship was more nearly linear, though these coefficients were not statistically significant (individually as coefficients on linear and quadratic terms or jointly). Meanwhile, African American choosers essentially showed indifference for own-group racial composition of schools.

The picture looked different for those applying to middle school entry grades (see Figure 1, middle panel), where all but the Hispanic group of applicants had a pronounced own-group preference and a slight preference for diversity, evidenced by curvature and a peak within the data at 50 percent. The bliss point, or optimal own-group percentage, was 26 percent for white applicants to middle school and 47 percent for African American applicants. In each figure, the curves are intentionally truncated, to avoid extrapolating beyond the range of observed own-group percentage for each group. The results for applicants to high school are shown in the bottom panel of Figure 1, which makes it clear that there was even less diversity of schools in terms of racial composition.

[16] We grouped Asian choosers, which made up one percent of applicants, together with white choosers and we grouped those who identified as "multiple/other" or missing, who together made up 16 percent of applicants, together with African American choosers. These groupings are arbitrary and did not change the conclusions when we put Asian, multiracial, and missing into a single omitted group of "other."

Figure 1. Own-race/ethnicity preferences, by race/ethnicity of chooser



Although there were some statistically significant interactions with other variables (significance results not show, but available from the authors), there were very few consistent patterns, and most of the preference parameters were of similar size and direction for all the race/ethnic groups. Exceptions at the elementary level were the demographic preferences, where coefficients for white choosers on own race/ethnicity and percentage low-income were significantly different from those of African American choosers. Coefficients for Hispanic choosers on percentage low-income and the accountability ratings were also significantly different from the correspondent coefficients for African American choosers.

Robustness

We examined several alternative functional forms to test the robustness of the main findings. In most cases, the general conclusions did not change a great deal. However, allowing for more interactions and more flexible nonlinearities in the relationships between attributes and utility led to some more nuanced findings.

Distance

It is plausible that preferences for a closer school are not linear. For example, there may be a mode-switching argument that a chooser first decides whether the prospective school is within walking range and then if not, considers sending the child to school in a car, bus, or train. The time cost of an extra half mile walk may be considerably more than the time cost of riding in a car, bus, or train for an additional half mile. Therefore, we estimated a piecewise linear model, with switching over at one mile. The estimates, shown for elementary schools in Table 8, suggest there is indeed a discrete penalty associated with switching from walking to riding, but that the per-mile penalty (slope of the relationship between distance and utility) decreases substantially beyond one mile. We also tested a quadratic model and models that used alternative measures of distance, including a straight-line measure and another that used mapping software to estimate the actual shortest-route travel distance. The alternative distance measures were highly correlated with each other, so, not surprisingly, the estimated preference weights were similar as well. In the quadratic model, the distance-squared term was statistically significant, although the degree of curvature was modest over the typical range of zero to six miles. The relationships shown in Table 8 pertain to elementary schools only. The results were similar for middle and high schools and are suppressed from Table 8 for brevity. The full results are presented in Figure C.1 in Appendix C.

Table 8. Alternative distance models (elementary entry grade applicants)

Variable	(1) Benchmark	(2) Right-angle distance	(3) Pierce-wise linear	(4) Straight-line distance	(5) Commuting distance from mapping software
On at least two bus lines	0.098***	0.102***	0.100***	0.098***	0.109***
On subway	0.113***	0.133***	0.142***	0.113***	0.114***
Distance, right-angle	-0.094***	-0.177***			
Distance squared, right-angle		0.010***			
Distance, if less than one mile			-0.688***		
Distance if greater than one mile			-0.068***		
Distance is greater than one mile (dummy)			-0.601***		
Distance, straight line				-0.124***	
Route distance from mapping software					
Route time from mapping software (minutes)					-0.104***
Sample size (student-school combinations)	**51,572**		**51,572**		**51,572**

Note: * $p < .05$, ** $p < .01$, *** $p < .001$. Variables other than distance included in the model, not shown here.

Academics

The data suggest that a school's academic performance is a statistically significant determinant of school preference, but there are several ways to measure academic performance, none of which consistently explains this relationship. The results presented in the benchmark model used four kinds of measures: proficiency rates varying from 0 to 100 percent, median growth percentile scores ranging from 0 to 100 as well, and two types of categorical accountability ratings – charter and state ratings, as discussed above.

To test the robustness of the benchmark model, we estimated several alternative specifications that each included one measure of school academic performance at a time: proficiency rate, growth score, indicators for each charter accountability rating, and indicators for each state accountability rating. These are shown in Table 9 for applicants to middle schools, the grade span where standardized tests are given in every grade. Similar results for applicants to elementary and high school grades are shown in Appendix C.

Table 9. Alternative measures of academic quality: Middle school entry grades (5 and 6)

School characteristics	Proficiency rate	Median growth percentile	Charter tier	ESEA classification	Proficiency and ESEA classification	Charter tier and ESEA classification
PROFICIENCY AND GROWTH						
Proficiency rate/10	0.11***					
Median growth percentile/10 (math)		-0.03*			0.06**	
CHARTER ACCOUNTABILITY						
PMF Tier 1 (charters only)			0.36***			0.23**
PMF Tier 2 (charters only)			0.21*			0.12
PMF Tier 3 (charter only) - omitted category			--0--			--0--
STATE ACCOUNTABILITY						
Reward				0.52***	0.32*	0.49***
Rising				0.18	0.05	0.18
Developing				0.29*	0.15	0.30*
Priority - omitted category				--0--	--0--	--0--
Focus				-0.25*	-0.32*	-0.24
Sample size (student-school combinations)	**9,045**		**9,045**		**9,045**	

Note: * $p < .05$, ** $p < .01$, *** $p < .001$; --0-- no p-value, parameter is constrained to zero. PMF is "Performance Management Framework," which is used to rate charter schools. ESEA is the Elementary and Secondary Education Act, for which schools receive an accountability index score. These scores are used to classify schools in the discrete categories used in the relevant regression specifications.

Model includes convenience, school demographics, school neighborhood and other school attributes, but coefficients are suppressed here. Corresponding results for elementary and high school entry grades are shown in Appendix C.

The findings presented in Table 9 as well as the findings in the appendix for other grade spans reinforce the conclusion that schools with better academic indicators are more likely to be ranked higher, although there were some exceptions. The statistically significant coefficient of 0.11 for proficiency rate, corresponding to an odds ratio of 1.12, was in line with the coefficients for elementary and high school (0.09 and 0.18, respectively). For growth percentile score, however, the coefficient was negative for middle school applicants (-0.03, significant at the 5 percent level), but positive for elementary school applicants (0.03) and high school applicants (0.14). The accountability categories all had coefficients that followed the expected pattern of higher categories being preferred. The size of the premium placed on higher ratings was greater for upper grades than lower grades, suggesting that non-academic factors weigh more heavily for parents of younger children. We also estimated models with more than one indicator together (as in the benchmark model) and separate models using continuous measures only or categorical measures (as dummy indicators). Those results are shown in Table C.8.

Endogeneity and independence of irrelevant alternatives

Parameter estimates from our approach provide suggestive information about the relative valuations families place on attributes of schools when choosing where to enroll their children. However, we note some threats to the validity of our estimates, which we summarize here and examine in more detail in Appendix B. Because distance to school is an endogenous factor in school choice for many families, we estimated our benchmark model omitting each applicant's top two school choices, arguing that applicants are likely unable to endogenously choose a household location with close proximity to more than one or two preferred schools. As shown in the appendix, the resulting estimates did not differ substantially from the main results, suggesting the potentially endogenous distance to schools is not a source of significant estimate bias.

We also investigated the plausibility of the rank-ordered logit model's implicit assumption of independence of irrelevant alternatives (IIA) in the context of school-choice sets.[17] First, we randomly excluded ranked school choices and jointly tested differences between the resulting parameter estimates and the estimates of our benchmark model, generating a distribution of test statistics. We also show in the appendix that the distribution of *p*-values from these iterative tests suggest our likelihood of rejecting the null that the two set of instruments are jointly different is only slightly higher than random chance.

Second, we compare our benchmark model estimates using the conditional logit with those from a mixed logit model, which does not inherently assume IIA. We find that the sign and significance of coefficient estimates generally do not change when relaxing IIA, with the exception of some statistically insignificant estimates that are close to zero. Together, these

[17] The IIA assumption is typically violated in cases where the choice set contains alternatives that are very similar to each other and individuals are indifferent between or hold very similar preference for these options. This is because the introduction of another option very similar to one of the original options should cause the probability of choosing that original option to be split between with the newly introduced similar option. A classic example is the discrete choice between modes of transportation that include a red train and a blue bus, each with equal probability of being chosen. Assuming the chooser cares only about the mode of transportation and is indifferent to the color of each vehicle, we would expect the introduction of a blue train option to maintain equal probabilities between choosing train or bus, with probabilities of 0.25 each for the red and blue trains. The logit model, however, would incorrectly predict equal probabilities of one-third for choosing each of the three options.

results suggest that if IIA violations do occur in the data, they do so relatively infrequently and are unlikely to introduce large errors in predicted choice probabilities.

IV. DISCUSSION AND CONCLUSION

Implications of choice preferences for stratification

We showed above that many attributes of schools influence how choosers rank their options. To better understand the implications of this pattern of preferences, we used the estimated parameters to predict how parents would rank schools under alternative scenarios. By using our model's predicted probabilities of selecting schools, we calculated the resulting distribution of students across schools if we were to relax all capacity constraints and allow everyone to attend his or her most preferred school. The resulting allocations of students to schools were then compared to the allocation that resulted under the status quo, which assigned students to their top choices, subject to a deferred-acceptance lottery to handle oversubscription. The predicted allocations under unrestricted choice (no capacity constraints) and status quo were also compared to that of a policy of neighborhood schools and to alternative policies in which we place restrictions on the choice sets. These restrictions simulate the effects of closing low-performing schools, for example, by simply removing those schools from the choice sets and predicting choices from among the remaining alternatives. Our model allows us to answer the following question: If we close a low-performing school, where would the parents who would have selected that school choose to attend instead?

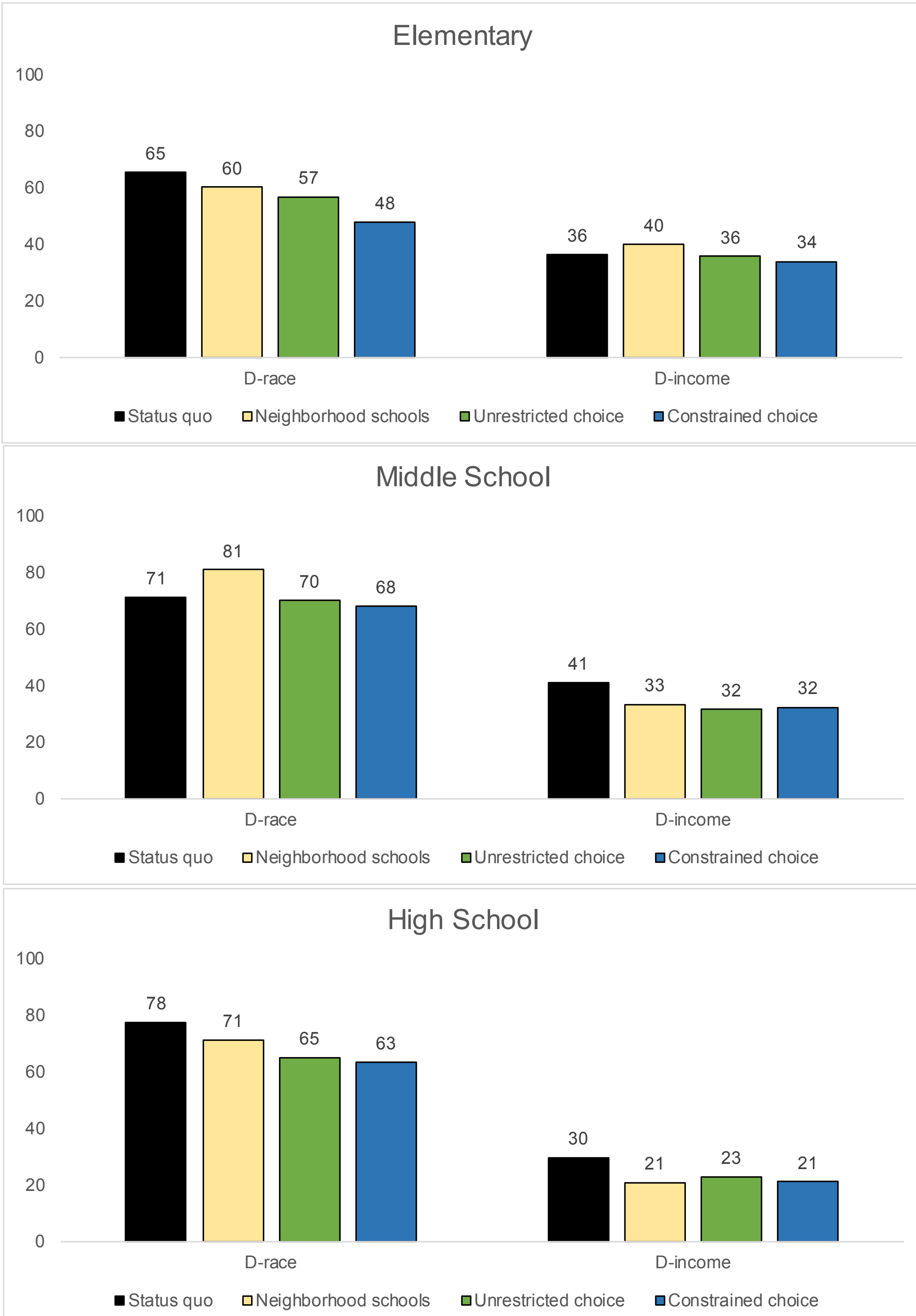
For each scenario, we defined outcome measures that summarize some aspect of the allocation of students to schools. One such outcome is the Index of Dissimilarity, or D-Index, which has been used to measure social stratification in a variety of contexts (Taueber and Taueber 1976).[18] The D-Index score for any binary measure, such as race, is defined as:

$$(5)\quad D = \frac{1}{2}\sum_{j=1}^{J}\left|\frac{w_j}{W} - \frac{n_j}{N}\right| x100$$

where w_j is the number of white students in school *j, W* is the number of white students in all schools, n_j is the number of nonwhite students in school *j,* an *N* is the number of nonwhite students in all schools. *D* ranges from a score of 0 for perfect integration to 100 for perfect segregation and can be interpreted as the percentage of students of a given group that would have to move to reproduce the overall fraction of each group in every individual school.

[18] The most common application has been residential segregation, where it was used to compare each individual neighborhood's racial composition to the overall composition of the population.

Figure 2. Race and income stratification under alternative policies

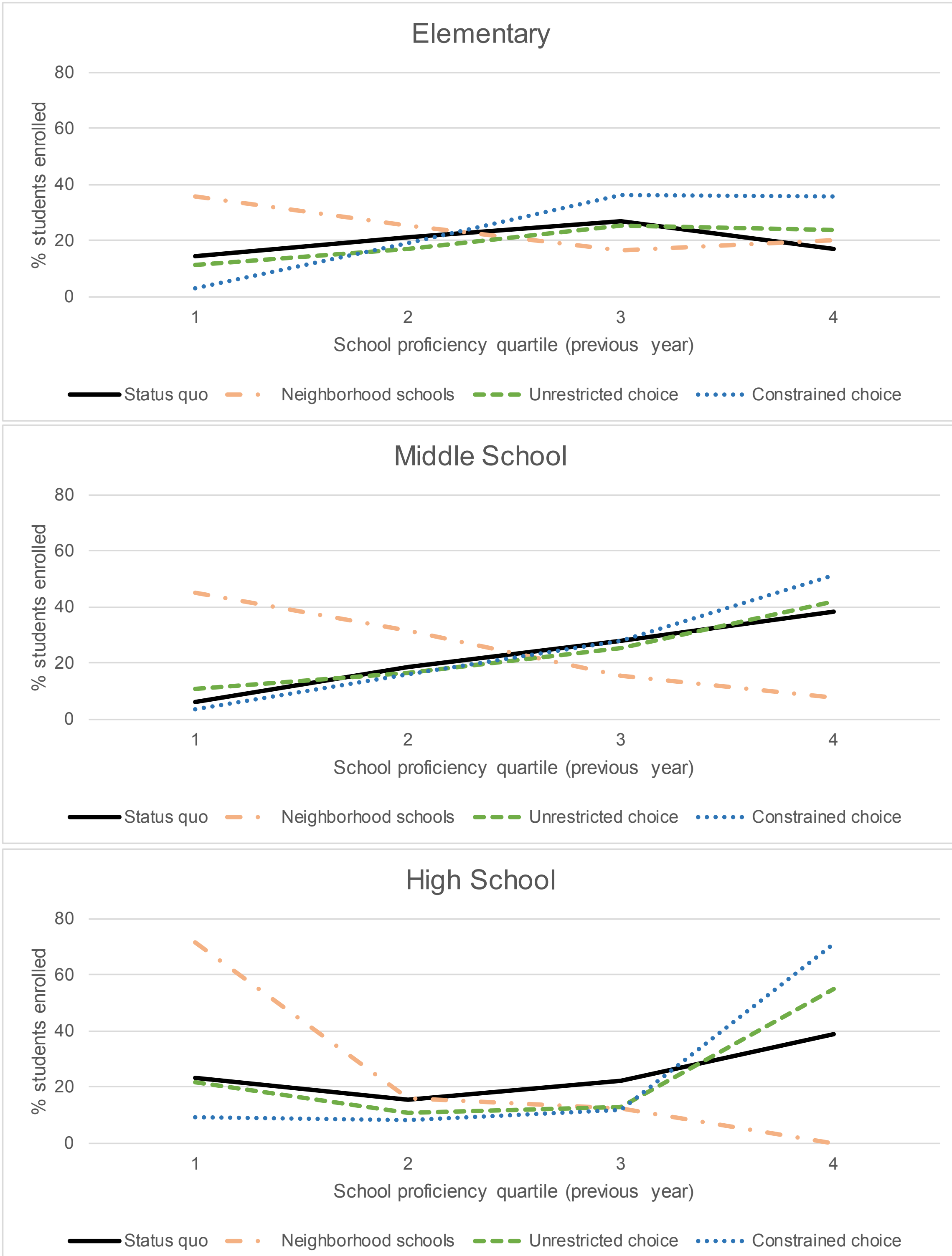


We calculated D-index scores for both race (white non-Hispanic and all others) and for income (direct certified as eligible for FRL meals or not direct certified). Results are shown in Figure 2, with elementary, middle, and high school results in the top, middle, and bottom panel, respectively. The figures show that under the status quo, the assignment process populates schools with a D-index of 65 for race and 36 for income at the elementary level. In other words, 65 percent of white students would have to be moved to achieve perfect balance by race, and 36 percent of direct-certified students would have to be moved to achieve perfect balance by income. Going to neighborhood schools, which would assign all applicants to their nearest by-right DCPS school (which excludes charter schools) would reduce the D-index for race from 65 to 60, but increase it for income from 36 to 40. If all applicants were offered their most preferred school listed on their applications without regard to capacity constraints (unrestricted choice), then the D-index scores would be lower still, 57 for race and 36 for income. However, our model predicts that if we constrain choices by removing the lowest-performing schools from the choice set, both D-index scores decline to 48 and 34 for race and income, respectively. A similar pattern holds for middle and high school, where constrained choice (eliminating the lowest-performing schools) produces the lowest levels of stratification of all the policy options considered, although not always very different from unrestricted choice.

We did not have information on choosers' ability levels and were therefore unable to examine the effects of different policies on sorting by ability. However, we did examine whether different policies would increase enrollment in schools that were higher- versus lower-performing in the year prior to the lottery. The analysis, summarized in Figure 3, shows that compared to assignments based on neighborhood catchment boundaries, school enrollments under the status quo lottery process result in many more middle and high school students attending schools with standardized testing proficiency rates in the top quartiles. For all grade levels, both unconstrained (predicted choices) and constrained choice (predicted choices in the absence of the lowest-performing schools) result in even greater shares of students attending schools with higher proficiency rates. Interestingly, with the exception of elementary, the constrained choice predictions produce results very similar to unconstrained choice. Taken together, these simulation results suggest that for students in tested grades, expanding school-choice capacity by making more spaces available at each campus would lead to additional movement of students toward schools with reputations for higher levels of academic achievement beyond that induced by the status quo school-choice process (though not necessarily higher levels of academic growth, as discussed in Section III).[19] The smaller differences between status quo, neighborhood schools, and unrestricted choice for elementary entry grades can be explained by the fact that some applicants chose schools that serve only early grade levels and therefore do not receive standardized testing proficiency rates. Additionally, parents may place a lower value on schools' academic achievement rates than on other attributes until their children are closer to entering a tested grade level.

[19] Whether this phenomenon extends to capacity expansion by replicating the model at other campuses was not directly testable.

Figure 3. Student enrollments by school proficiency quartiles under alternative school choice policies



Note: Elementary percentages do not sum to 100, as some school choice options for elementary entry grades do not serve tested grade levels and therefore do not correspond to proficiency rates.

The simulation methods used here can be extended in a number of other ways. One can place other restrictions on choice sets and examine resulting enrollment patterns from any number of perspectives, such as an individual school or school type, including enrollment by different subgroups of students. One can also simulate the effects over time. We examined the effect of updating the student body composition after predicting enrollment outcomes for unrestricted choice and repeating the prediction exercise until a steady-state equilibrium was reached. This steady-state analysis converged after approximately five iterations, with further iterations not generating substantially different predictions, so we did not report findings after five iterations here. In theory, however, long-run re-sorting can take place over time as choosers adjust to the changing demographic composition of the school (see Glazerman 1998).

Contributions, limitations, and future research

The number of U.S. cities that have adopted, are soon to adopt, or are considering adopting centralized application and assignment systems is growing rapidly.[20] Part of this growth is stimulated by the expansion of charter schools and the need to rationalize the large numbers of parallel school admissions processes for parents and school administrators. With this growth, there will come more and better applicant data to understand consumer preferences. The current study provides an example of how applicant data can be used to better understand the preferences of parents when there is a marketplace of schools.

Some important qualifications and limitations are necessary to keep in mind when interpreting the findings from this study and others like it. First, we necessarily focus on those who chose to participate in the lottery. In DC, as in most settings, there is a default school or a secondary assignment process that takes place after the lottery deadlines have passed, in which large numbers of students would enroll in schools that have available space. Sorting outcomes may depend critically on who declines or fails to participate in the choice system, so a worthwhile focus of future research would be the factors that affect choice along this margin.

Another limitation is that we treat residential location as exogenous to the school-choice decision. A third limitation has to do with important unobserved variables. We did not have data on students' own academic ability, nor did we have information on choosers' attributes that might predict preference for special programs like music, sports, or special services. Access to these variables, which were shown by Harris and Larsen (2015) to be relevant in New Orleans, could improve the fit and predictive power of the model and reduce the amount of unobserved idiosyncratic heterogeneity.

Our finding in this paper that rankings of lower-income choosers were explained by different indicators than higher-income choosers is consistent with the theory of search costs, suggesting that there may be barriers to obtaining information about certain school attributes. However, we note that all of the inferences made in this paper are conditional on a particular static information regime. That is, we can describe what information was readily available to choosers and what information would have been more difficult to obtain, but cannot easily model

[20] See, for example: Rich, Motoko. "Oakland District at Heart of Drive to Transform Urban Schools." The *New York Times,* March 4, 2016. Available at http://www.nytimes.com/2016/03/05/education/oakland-district-at-heart-of-drive-to-transform-urban-schools.html. Accessed March 8, 2016.

how outcomes would change under alternative information regimes. If policymakers were to change that balance, for example, by lowering the cost of learning about idiosyncratic school characteristics or academic quality, then those attributes might be more influential. A fruitful area for future research would be conducting information experiments, wherein policies are tested that might reduce search costs or the costs of learning about schools or particular school attributes.

In conclusion, the basis of competition in a school choice system might be any number of things simultaneously—academics, convenience, demographics—but quantifying the relative strength of parental preferences for these attributes provides a basis for making important and useful predictions about behavioral responses to policy changes.

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APPENDIX A. FINDINGS ON NEIGHBORHOOD AND OTHER NON-ACADEMIC CHARACTERISTICS

The main results focused on convenience, academics, and school demographics. However, several other variables were included in the models. Here we discuss school neighborhood characteristics as well as certain other school offerings and amenities for which data were available on the school profiles. In Table A.1, we present a more detailed listing of coefficients from the benchmark model by entry grade. It is the same as Table 4 in the body of the report, but includes the benchmark coefficients for school neighborhood and other attributes. The *other school attributes* listed in Table A.1 are measured only for DCPS schools, so their values are set to zero for charter schools, and a dummy variable was included to account for these schools with missing values.

We constructed two types of relative neighborhood characteristics measures. One type subtracts the value of the chooser's own neighborhood characteristic from each school value, measuring, for example, whether the school is in a neighborhood (Census block group) that has higher poverty or much higher poverty than one's own neighborhood. The other measure is the absolute value of that difference, which assumes the chooser is indifferent between a school in a neighborhood that has a much higher poverty rate and a school whose neighborhood has a much lower poverty rate compared to one's own neighborhood.

The results of the alternative models, shown in Table A.2, suggest that, on average, applicants do not consistently favor schools located in higher SES neighborhoods. For applicants to elementary schools (top panel), the coefficients on percentages with college degree and children in poverty suggest applicants favor lower SES (fewer college graduates and more children in poverty). For middle schools, only the coefficients on both household income and housing costs are positive and statistically significant at the 1 percent level, suggesting middle school applicants favor schools in higher SES neighborhoods. On average, applicants to high schools ranked schools higher if they were in neighborhoods with higher percentages of African American residents and higher percentages of children in poverty. On the other hand, the negative and statistically significant coefficients on the percentage of households receiving public assistance for elementary and high schools is suggestive of applicants favoring schools in higher SES neighborhoods.

Some other results were counterintuitive as well. The coefficient on crime rates should be negative if we assume that parents prefer schools in safer neighborhoods. This was the case for property crime, but the coefficient was positive and significant for violent crime in elementary and high school entry grades. This was a robust result and not just the result of multicollinearity. There was no obvious explanation for this finding, although we examined the relationship of violent crime rates with other neighborhood variables and found that this characteristic was associated with high density and not with neighborhood income.

Another possible explanation is differential under-reporting of violent crime. This would explain the findings if more desirable neighborhoods were those where violent crimes were reported at higher rates than in less desirable ones, despite being less prevalent. Unfortunately, evidence from a more objective source, gunshots recorded by special technology called ShotSpotter, aligned with the crime data we used. An Urban Institute analysis of gunshots fired near DC schools found that 9 percent of schools accounted for nearly half of all gunfire incidents during the period studied. The four schools closest to the highest volume of gunfire were charter schools in the DC's northwest quadrant (Bieler and LaVigne 2014), where all 12 of the city's 12 wealthiest neighborhoods are located (Paschall 2014).

Table. A.1. Rank-ordered logit results, full benchmark model

	Applicants entering		
School characteristics	**Elementary school**	**Middle school**	**High school**
CONVENIENCE			
Distance (miles)	-0.094 ***	-0.057 ***	-0.021 **
On at least two bus lines	0.098 ***	0.225 ***	0.043
On subway	0.113 ***	0.063	0.136 *
SCHOOL DEMOGRAPHICS			
Own-race percentage/10	0.061 ***	0.163 ***	0.172 ***
Own-race percentage/10 squared	-0.002	-0.016 ***	-0.001 **
Percentage low income (direct-certified)/10	-0.161 ***	0.149 ***	0.038
ACADEMICS—PROFICIENCY AND GROWTH			
Proficiency rate/10	0.085 ***	0.070 **	0.143 ***
Median growth percentile/10 (math)	-0.008	-0.111 ***	-0.196 ***
ACADEMICS—CHARTER SCHOOL ACCOUNTABILITY RATING			
PMF Tier 1 (charters only)	0.101	0.228	-0.292 *
PMF Tier 2 (charters only)	-0.003	0.028	-0.019
PMF Tier 3 (charter only) - omitted category	--0--	--0--	--0--
ACADEMICS—STATE ACCOUNTABILITY RATING			
1. Reward	0.061	0.383 **	1.204 ***
2. Rising	-0.028	0.121	0.541 ***
3. Developing	0.011	0.138	0.296 *
4. Priority - omitted category	--0--	--0--	--0--
Focus school: subgroup gaps	0.007	-0.262 *	0.114
SCHOOL NEIGHBORHOOD			
Crime rate, violent crimes/month	0.230***	-0.088	0.283**
Crime rate, property crimes/month	-0.045***	-0.001	-0.141***
Log (household income)	-0.062***	0.082	0.098
OTHER SCHOOL ATTRIBUTES (TRADITIONAL SCHOOLS ONLY)			
Average core class size (number of students)	0.018***	0.027*	-0.007
Requires school uniforms	-0.307***	0.065	-0.010
Has before-care programs	0.139***	-0.132	--
Has after-school programs	-0.085**	-0.079	0.086
OTHER CONTROL VARIABLES			
Sibling indicator	Included	Included	Included
Sector indicator (charter versus traditional)	Included	Included	Included
Indicators for missing school attributes	Included	Included	Included
Sample size (student-school combinations)	**51,572**	**9,045**	**11,543**

Notes: * $p < .05$, ** $p < .01$, *** $p < .001$; --0-- no p-value, parameter is constrained to zero.

Variables with "/10" can be interpreted as one unit representing 10 percentage points.

PMF is "Performance Management Framework," which is used to rate charter schools.

Sample for each column is applicants to entry grades for the respective school level: Pre-K and kindergarten for elementary, grades 5 and 6 for middle school, and grade 9 for high school.

Table. A.2. Alternative neighborhood characteristics models

Neighborhood Variable	Benchmark	Long model	Chooser-school differences	Absolute differences
Applicants to elementary school				
Gini coefficient		-0.406***		
Log (median household income)	-0.062***	0.043		
Median family income			-0.000	-0.000
Percentage with college degree		-0.423***	-0.246***	-0.184***
Median housing costs		-0.000*	-0.000	-0.000*
Percent African American		-0.098	-0.072	-0.039
Percentage of school-age children in poverty		0.351***	0.282***	-0.038
Percentage receiving public assistance		-0.417***	-0.439***	-0.027
N (student-school combinations)	51,572	51,572	50,633	50,633
Applicants to middle school				
Gini coefficient		-0.113		
Log (median household income)	0.082	0.248**		
Median family income			0.000	-0.000
Percentage with college degree		-0.460*	-0.005	-0.248
Median housing costs		0.000	0.000**	0.000**
Percent African American		0.075	0.157	0.089
Percentage of school-age children in poverty		0.415	0.478*	0.019
Percentage receiving public assistance		0.112	0.155	0.086
N (student-school combinations)	9,045	9,045	8,926	8,926
Applicants to high school				
Gini coefficient		-0.151		
Log (median household income)	0.098	0.798***		
Median family income			0.000***	-0.000
Percentage with college degree		-1.589***	-2.591***	0.179
Median housing costs		0.000	-0.000*	-0.000*
Percent African American		2.092***	2.548***	-0.092
Percentage of school-age children in poverty		1.081**	1.630***	0.363*
Percentage receiving public assistance		-1.355***	-2.343***	-0.136
Sample size (student-school combinations)	**11,543**	**11,543**	**10,362**	**10,362**

Notes: * $p < .05$, ** $p < .01$, *** $p < .001$. Variables other than neighborhood included in the model, not shown here. The estimation sample for each panel consists of applicants to entry grades for the respective school level: Pre-K and kindergarten for elementary, grades 5 and 6 for middle school, and grade 9 for high school.

A third explanation for the crime results is that crime perceptions may differ from reported crime rates. We did not have access to crime perceptions data, but we should note that the crime data and Census data we used for this analysis was not part of the information reported to parents as part of ample information provided by the city.

We also included neighborhood income. This was measured as the log of the median household income for the Census block group in which the school was located. For choosers applying to elementary schools, we found a negative relationship, suggesting that, all things being equal, parents ranked schools higher if they were in lower-income neighborhoods.

One possible interpretation of the school neighborhood findings taken together (including the preference for higher violent crime rates) is that families do indeed choose schools without regard to the neighborhood characteristics or choose schools in neighborhoods with *lower* SES. In fact, one hypothesis would hold that if charter schools have difficulty finding facilities, then they would tend to be located in the least desirable real estate markets in the city (Brown 2014), and those that invested most heavily in academic programs and least in facilities would be in even less desirable real estate markets, creating the observed negative relationship between neighborhood quality and unobserved (to the researcher) school quality.

The other set of counterintuitive results has to do with the "other school amenities." Contrary to what one might expect, choosers entering elementary or middle school were *more* likely to choose a school with larger average class size. There are two possible explanations for this. One explanation would be a version of reverse causality: popular schools enroll more students, making it harder to maintain low class sizes. Because a school's budget is typically tied to its enrollment, this is not a likely explanation for long-term trends. Another explanation is that schools with larger class sizes may be investing more in other amenities that parents value more.

Schools that required students to wear a uniform were less likely to be ranked higher at the elementary school level. Coefficients on indicators for whether before- and after-school care were available, which are most relevant for elementary and middle school, were not consistent, although we note that program offerings at a school that serves both elementary and middle school grades but are open to younger students may not be relevant for middle school choosers applying to that school.

APPENDIX B. DETAILED ANALYSIS OF ENDOGENEITY AND INDEPENDENCE OF IRRELEVANT ALTERNATIVES

Parameter estimates from our approach provide suggestive information about the relative valuations families place on attributes of schools when choosing where to enroll their children. However, we note several reasons to exercise caution when drawing inference from the results. First, distance from household to school is an endogenous factor in school choice for many families, as access to quality schools is often a key factor in household location. Second, there is the possibility of strategic behavior on the part of applicants that could lead to applicants' submitted school rankings representing an order other than their preferences among schools in the DC. Third, violation of the independence of irrelevant alternatives assumption that is implicit to the rank-ordered logit model could result in estimates that generate predicted probabilities of choice with large error for some schools in the choice set. In the following subsections, we discuss each of these potential issues and explore the extent to which they may influence the main results of this paper.

Endogeneity of distance to school

If families do locate near preferred schools, we would expect the relationship between proximity and the desirability of schools to be explained—at least partially—by this behavior, rather than by preferences for proximity alone. To shed light on the extent to which this is the case, we estimate the benchmark model omitting each applicant's top two school choices, arguing that applicants are likely unable to endogenously choose a household location with close proximity to more than one or two preferred schools. The results for elementary entry grades are shown in Table B.1, where the pattern of estimates when excluding the top two school choices (column 2) generally follows that of the estimates in column 1 that include all choices, but restrict the sample to applicants who ranked more than two schools to avoid differences due to a changing pool of applicants. For comparison, column 3 presents estimates for the same sample of applicants, but school choices restricted to the three highest-ranked schools. The association between school choice and distance to the school is slightly larger for higher-ranked schools and slightly lower for lower-ranked schools. Additionally, charter school tier rankings are not positively associated with the highest-ranked schools. This may be driven by the fact that all families planning to enroll children in pre-kindergarten had to submit an application even for their in-boundary public school, resulting in the pre-kindergarten applicants being the only group to submit applications ranking their nearest public school. Otherwise, the pattern of coefficient estimates for these truncated choice sets do not differ substantially from the main results, suggesting the potentially endogenous distance to schools is not a source of significant estimate bias. In Tables B.2 and B.3, we present analogous results for middle and high school entry grades, respectively, which show a similar pattern. We note that some coefficient estimates are slightly smaller and no longer statistically significant because of limited power from the resulting smaller estimation sample after truncating choice sets.

Table. B.1. Alternative choice sets: Elementary

School characteristics	Choice set: Benchmark model	Choice set: Excluding top 2 choices	Choice set: Only top 3 choices
CONVENIENCE			
Distance (miles)	-0.094***	-0.057***	-0.124***
On at least two bus lines	0.094***	0.082***	0.099**
On subway	0.120***	0.054*	0.194***
SCHOOL DEMOGRAPHICS			
Own-race percentage/10	0.059***	0.039**	0.087***
Own-race percentage/10 squared	-0.001	-0.000	-0.005
Percentage low income (direct-certified)/10	-0.165***	-0.111***	-0.185***
SCHOOL NEIGHBORHOOD			
Crime rate, violent crimes/month	0.236***	0.164***	0.183***
Crime rate, property crimes/month	-0.046***	-0.026***	-0.050***
Log (household income)	-0.064***	-0.020	-0.083*
ACADEMICS—PROFICIENCY AND GROWTH			
Proficiency rate/10	0.084***	0.078***	0.027
Median growth percentile/10 (math)	-0.009	-0.007	0.003
ACADEMICS—-CHARTER SCHOOL ACCOUNTABILITY RATING			
PMF Tier 1 (charters only)	0.126*	0.171**	-0.140
PMF Tier 2 (charters only)	0.028	0.092	-0.177
PMF Tier 3 (charter only) - omitted category	--0--	--0--	--0--
ACADEMICS—STATE ACCOUNTABILITY RATING			
1. Reward	0.065	0.009	0.184
2. Rising	-0.026	-0.065	0.067
3. Developing	0.006	-0.051	0.042
4. Priority - omitted category	--0--	--0--	--0--
Focus school: subgroup gaps	0.002	-0.030	0.014
OTHER SCHOOL ATTRIBUTES (TRADITIONAL SCHOOLS ONLY)			
Average core class size (number of students)	0.018***	0.021***	-0.002
Requires school uniforms	-0.306***	-0.283***	-0.129*
Has before-care programs	0.143***	0.090**	0.203***
Has after-school programs	-0.086**	-0.065*	-0.158**
Sample size (student-school combinations)	**46,544**	**32,976**	**20,352**

Notes: * $p < .05$, ** $p < .01$, *** $p < .001$; --0-- no *p*-value, parameter is constrained to zero.

To maintain a consistent pool of applicants when producing estimates under the three choice sets reported, the estimation sample is restricted to applicants who ranked at least three schools.

PMF is “Performance Management Framework,” which is used to rate charter schools. The estimation sample for each column consists of applicants to elementary entry grades pre-K and kindergarten.

Table. B.2. Alternative choice sets: Middle school

School characteristics	Choice set		
	All school choices	Excluding top 2 choices	Only top 3 choices
CONVENIENCE			
Distance (miles)	-0.055***	-0.045***	-0.026
On at least two bus lines	0.171***	0.186**	-0.066
On subway	0.058	-0.028	0.171
SCHOOL DEMOGRAPHICS			
Own-race percentage/10	0.152***	0.090*	0.135*
Own-race percentage/10 squared	-0.015***	-0.009*	-0.015*
Percentage low income (direct-certified)/10	0.160***	0.131***	0.058
SCHOOL NEIGHBORHOOD			
Crime rate, violent crimes/month	-0.087	0.077	-0.171
Crime rate, property crimes/month	0.002	-0.011	-0.010
Log (household income)	0.091*	0.159**	-0.145
ACADEMICS—PROFICIENCY AND GROWTH			
Proficiency rate/10	0.082**	0.049	0.114*
Median growth percentile/10 (math)	-0.105***	-0.036	-0.130***
ACADEMICS—CHARTER SCHOOL ACCOUNTABILITY RATING			
PMF Tier 1 (charters only)	0.203	0.179	-0.234
PMF Tier 2 (charters only)	0.003	0.032	-0.374
PMF Tier 3 (charter only) - omitted category	--0--	--0--	--0--
ACADEMICS—STATE ACCOUNTABILITY RATING			
1. Reward	0.374**	0.306	0.327
2. Rising	0.116	0.116	0.160
3. Developing	0.145	0.112	0.103
4. Priority - omitted category	--0--	--0--	--0--
Focus school: Subgroup gaps	-0.244	-0.056	-0.318
OTHER SCHOOL ATTRIBUTES (TRADITIONAL SCHOOLS ONLY)			
Average core class size (number of students)	0.024 *	0.028*	0.038
Requires school uniforms	0.077	0.078	0.321
Has before-care programs	-0.130	0.040	-0.399**
Has after-school programs	-0.074	-0.103	0.048
Sample size (student-school combinations)	**7,503**	**4,937**	**3,849**

Notes: * $p < .05$, ** $p < .01$, *** $p < .001$; --0-- no *p*-value, parameter is constrained to zero.

To maintain a consistent pool of applicants when producing estimates under the three choice sets reported, the estimation sample is restricted to applicants who ranked at least three schools.

PMF is “Performance Management Framework,” which is used to rate charter schools. The estimation sample for each column consists of applicants to grades 5 and 6—common middle school entry grades for DC schools.

Table. B.3. Alternative choice sets: High school

School characteristics	Choice set: All school choices	Choice set: Excluding top 2 choices	Choice set: Only top 3 choices
CONVENIENCE			
Distance (miles)	-0.020**	-0.013	-0.018
On at least two bus lines	0.013	-0.157	0.345**
On subway	0.155*	0.232**	0.079
SCHOOL DEMOGRAPHICS			
Own-race percentage/10	0.172***	0.130*	0.146*
Own-race percentage/10 squared	-0.010**	-0.009	-0.005
Percentage low income (direct-certified)/10	0.048	0.038	0.023
SCHOOL NEIGHBORHOOD			
Crime rate, violent crimes/month	0.227*	-0.135	0.538**
Crime rate, property crimes/month	-0.132***	-0.044	-0.186**
Log (household income)	0.077	-0.119	0.299**
ACADEMICS—PROFICIENCY AND GROWTH			
Proficiency rate/10	0.138***	0.082**	0.123**
Median growth percentile/10 (math)	-0.190***	-0.103*	-0.168**
ACADEMICS—CHARTER SCHOOL ACCOUNTABILITY RATING			
PMF Tier 1 (charters only)	-0.276*	-0.030	-0.600*
PMF Tier 2 (charters only)	-0.035	-0.036	-0.191
PMF Tier 3 (charter only) - omitted category	--0--	--0--	--0--
ACADEMICS—STATE ACCOUNTABILITY RATING			
1. Reward	1.203***	0.633**	1.348***
2. Rising	0.527***	0.268	0.766***
3. Developing	0.319*	0.526**	0.134
4. Priority - omitted category	--0--	--0--	--0--
Focus school: subgroup gaps	0.108	-0.068	0.300
OTHER SCHOOL ATTRIBUTES (TRADITIONAL SCHOOLS ONLY)			
Average core class size (number of students)	-0.004	0.047*	-0.038
Requires school uniforms	0.004	0.055	-0.254
Has after-school programs	0.079	0.039	0.168
Sample size (student-school combinations)	**10,032**	**6,172**	**5,790**

Notes: * $p < .05$, ** $p < .01$, *** $p < .001$; --0-- no p-value, parameter is constrained to zero.

To maintain a consistent pool of applicants when producing estimates under the three choice sets reported, the estimation sample is restricted to applicants who ranked at least three schools.

PMF is “Performance Management Framework,” which is used to rate charter schools. The estimation sample for each column consists of applicants to grade 9—the common high school entry grade for DC schools.

Independence of irrelevant alternatives assumption

We explore the plausibility of the rank-ordered logit model's implicit assumption of independence of irrelevant alternatives (IIA) in the context of school choice. For this assumption to hold, the relative odds of one school being chosen over another is independent of the attributes of a third school option.[21] We investigate whether IIA is likely to be violated in two ways. We first test the validity of the IIA assumption within our sample by randomly excluding ranked school choices and jointly test whether differences between the resulting parameter estimates and the estimates of our benchmark model are statistically significant. Using this method, we perform a bootstrap-style test in which we iteratively randomize choice exclusions from the estimation procedure and jointly test these differences, generating a distribution of test statistics. In Table B.4, we present the results of this exercise. Using a significance level of 0.05, we should expect to reject the null hypothesis that excluding choice does not produce significantly different sets of coefficient estimates for 5 percent of iterations, on average. In practice, we reject this null hypothesis slightly more often. Nearly 12 percent of our trials result in rejecting the null at the 5 percent level, which suggests IIA may not be strictly upheld in all cases.

Table. B.4. Tests of the independence of irrelevant alternatives assumption

	p-values	
Percentile	One choice randomly excluded	Two choices randomly excluded
5th percentile	0.021	0.019
10th percentile	0.038	0.039
25th percentile	0.126	0.119
50th percentile	0.313	0.292
75th percentile	0.561	0.551
90th percentile	0.077	0.765
95th percentile	0.881	0.848
% iterations with $p < 0.05$	11.9%	11.6%

Notes: Statistics reported are *p*-values and corresponding percentiles from a distribution of test statistics. These test statistics are from 1,000 iterations, each randomly excluding one or two school choices per applicant before producing estimates from our benchmark model. Differences between the resulting estimates and estimates from the benchmark model were then jointly tested to produce that iterations test statistic.

[21] The IIA assumption is typically violated in cases where the choice set contains alternatives that are very similar to each other and individuals are indifferent between (or hold very close preferences for) these options. This is because the introduction of another option very similar to one of the original options should cause the probability of choosing that original option to be split between with the newly introduced similar option. A classic example is the discrete choice between modes of transportation that include a red train and a blue bus, each with equal probability of being chosen. Assuming the chooser cares only about the mode of transportation and is indifferent to the color of each vehicle, we would expect the introduction of a blue train option to maintain equal probabilities between choosing train or bus, with probabilities of 0.25 each for the red and blue trains. The logit model, however, would incorrectly predict equal probabilities of one-third for choosing each of the three options.

We further investigated the extent to which violations of IIA might influence our results by relaxing the IIA assumption. We compare estimates of our benchmark model with estimates using a mixed-logit model, which does not inherently assume IIA, and find very similar results that suggest the IIA assumption is not broadly inappropriate. The mixed-logit approach, however, is limited in that it models a singular binary choice and estimates parameters by differentiating first-ranked schools from all others rather than using the more complete information contained in applicants' relative rankings of chosen schools. To make a more direct comparison of estimates with and without an implicit assumption of IIA, we compare the mixed-logit estimates to estimates from a conditional logit model of first-ranked schools, which also models a singular choice of a first-ranked school, but does assume IIA. In Table B.5, we present estimates for the benchmark set of covariates from each model type for the elementary entry grades. Columns 1 and 2 show estimates from a rank-ordered logit and conditional logit, respectively. Columns 3 and 4 show mixed-logit estimates, where column 3 models school academic indicators with random, applicant-specific coefficients, and column 4 does so for school neighborhood characteristics. Means of the distribution of these random coefficients are reported, with standard deviations below. Comparing columns 1 and 2, coefficients for the conditional logit estimation are predictably larger than those of the rank-ordered logit, as the rank-ordered logit accounts for differences between first- and second-ranked schools, second- and third-ranked schools, and so on, which are likely to be less dramatic than the differences between first-ranked schools and schools with very low preference rakings that are utilized by the conditional logit. Comparing column 2 to columns 3 and 4, we note that the sign and significance of coefficient estimates generally do not change when moving to a mixed logit model that relaxes IIA, with the exception of some statistically insignificant estimates that are close to zero. Indeed, the magnitudes of coefficient estimates are generally the same between these two approaches, with the exception of the accountability rating category coefficients, which increase in magnitude relative to the priority category for reward, rising, and focus. Identical comparisons for middle and high school, presented in Tables B.6 and B.7, yield similar patterns, though the mixed logit accountability category coefficients generally decrease relative to those of the conditional logit model.

Heterogeneity of preferences for school quality

Modeling parental preferences using a mixed logit approach also provides information on the extent to which applicants exhibit heterogeneity in their preferences for various school attributes. Column 3 of Tables B.5 through B.7 allow for applicant heterogeneity in preferences for school academic indicators, where random coefficient means are reported for indicators of school academic quality, with estimated coefficient standard deviations in brackets. The distributions of these random coefficients provide insight on the amount of heterogeneity that exists in the relationship between indicators of school quality and school preferences.

Table. B.5. Alternate logit specifications: Elementary

School characteristics	Rank-ordered logit	Conditional logit	Mixed logit (1)	Mixed logit (2)
CONVENIENCE				
Distance (miles)	-0.094***	-0.229***	-0.244***	-0.229***
On at least two bus lines	0.098***	0.203***	0.160***	0.124**
On subway	0.113***	0.316***	0.265***	0.239***
SCHOOL DEMOGRAPHICS				
Own-race percentage/10	0.061***	0.145***	0.121***	0.122***
Own-race percentage/10 squared	-0.002	-0.008**	-0.005	-0.006*
Percentage low income (direct-certified)/10	-0.161***	-0.313***	-0.326***	-0.305***
ACADEMICS—PROFICIENCY AND GROWTH				
Proficiency rate/10	0.085***	0.110***	0.113***	0.126***
[Random coefficient std. dev.]			[0.187]***	
Median growth percentile/10 (math)	-0.008	0.003	-0.001	0.002
[Random coefficient std. dev.]			[0.024]	
ACADEMICS—CHARTER SCHOOL ACCOUNTABILITY RATING				
PMF Tier 1 (charters only)	0.101	-0.205	-0.135	-0.200
[Random coefficient std. dev.]			[0.082]	
PMF Tier 2 (charters only)	-0.003	-0.313**	-0.408**	-0.315**
[Random coefficient std. dev.]			[0.850]***	
PMF Tier 3 (charter only) - omitted category	--0--	--0--	--0--	--0--
ACADEMICS—STATE ACCOUNTABILITY RATING				
Reward	0.061	0.134	0.278*	0.183
[Random coefficient std. dev.]			[0.020]	
Rising	-0.028	-0.007	0.118	0.067
[Random coefficient std. dev.]			[0.578]*	
Developing	0.011	0.153	0.033	0.212*
[Random coefficient std. dev.]			[1.073]***	
Priority - omitted category	--0--	--0--	--0--	--0--
Focus	0.007	-0.005	0.099	0.142
[Random coefficient std. dev.]			[0.618]**	
SCHOOL NEIGHBORHOOD				
Crime rate, violent crimes/month	0.230***	0.359***	0.328***	0.283***
[Random coefficient std. dev.]				[0.344]*
Crime rate, property crimes/month	-0.045***	-0.103***	-0.095***	-0.090***
[Random coefficient std. dev.]				[0.003]
Log (household income)	-0.062***	-0.136**	-0.181***	-0.168***
[Random coefficient std. dev.]				[0.008]
OTHER SCHOOL ATTRIBUTES (TRADITIONAL SCHOOLS ONLY)				
Average core class size (number of students)	0.018 ***	0.019*	0.018	0.020*
Requires school uniforms	-0.307 ***	-0.353***	-0.421***	-0.350***
Has before-care programs	0.139 ***	0.219***	0.215**	0.192**
Has after-school programs	-0.085 **	-0.126	-0.138	-0.105
Sample size (student-school combinations)	51,572	49,376	49,376	49,376

Notes: Estimates presented are generated from rank-ordered logit (column 1), conditional logit (column 2), and mixed-logit (columns 3 and 4) specifications. Column 3 is a mixed-logit model of heterogeneous preferences for academic quality, while column 4 models heterogeneous preferences for school neighborhood characteristics. The estimation sample for each column consists of applicants to elementary entry grades pre-K and kindergarten.

* *p* < .05, ** *p* < .01, *** *p* < .001, --0-- no *p*-value, parameter is constrained to zero.

PMF is “Performance Management Framework,” which is used to rate charter schools.

Table. B.6. Alternate logit specifications: Middle school

School characteristics	Rank-ordered logit	Conditional logit	Mixed logit (1)	Mixed logit (2)
CONVENIENCE				
Distance (miles)	-0.057***	-0.089***	-0.093***	-0.092***
On at least two bus lines	0.225***	0.304**	0.287**	0.293**
On subway	0.063	0.317**	0.382**	0.341**
SCHOOL DEMOGRAPHICS				
Own-race percentage/10	0.163***	0.261***	0.256**	0.230**
Own-race percentage/10 squared	-0.016***	-0.025***	-0.027***	-0.024***
Percentage low income (direct-certified)/10	0.149***	0.120	0.194*	0.154*
ACADEMICS—PROFICIENCY AND GROWTH				
Proficiency rate/10	0.070**	0.092	0.145*	0.130*
[Random coefficient std. dev.]			[0.024]	
Median growth percentile/10 (math)	-0.111***	-0.215***	-0.271***	-0.219***
[Random coefficient std. dev.]			[0.236]	
ACADEMICS—CHARTER SCHOOL ACCOUNTABILITY RATING				
PMF Tier 1 (charters only)	0.228	0.029	0.110	0.163
[Random coefficient std. dev.]			[0.250]	
PMF Tier 2 (charters only)	0.028	-0.253	-0.494	-0.169
[Random coefficient std. dev.]			[1.591]***	
PMF Tier 3 (charter only) - omitted category	--0--	--0--	--0--	--0--
ACADEMICS—STATE ACCOUNTABILITY RATING				
Reward	0.383**	0.502	0.165	0.110
[Random coefficient std. dev.]			[-0.147]	
Rising	0.121	0.194	-0.154	-0.166
[Random coefficient std. dev.]			[-0.761]*	
Developing	0.138	0.206	0.020	0.052
[Random coefficient std. dev.]			[0.112]	
Priority - omitted category	--0--	--0--	--0--	--0--
Focus	-0.262*	-0.545	-1.032**	-0.897**
[Random coefficient std. dev.]			[-0.003]	
SCHOOL NEIGHBORHOOD				
Crime rate, violent crimes/month	-0.088	-0.208	-0.388*	-0.419**
[Random coefficient std. dev.]				[-0.558]
Crime rate, property crimes/month	-0.001	-0.022	-0.009	-0.006
[Random coefficient std. dev.]				[0.074]
Log (household income)	0.082	-0.067	-0.092	-0.092
[Random coefficient std. dev.]				[-0.070]
OTHER SCHOOL ATTRIBUTES (TRADITIONAL SCHOOLS ONLY)				
Average core class size (number of students)	0.027*	0.076**	0.067*	0.062*
Requires school uniforms	0.065	0.193	0.197	0.205
Has before-care programs	-0.132	-0.418*	-0.444*	-0.458**
Has after-school programs	-0.079	-0.166	-0.175	-0.164
Sample size (student-school combinations)	**9,045**	**8,431**	**8,431**	**8,431**

Notes: Estimates presented are generated from rank-ordered logit (column 1), conditional logit (column 2), and mixed-logit (columns 3 and 4) specifications. Column 3 is a mixed-logit model of heterogeneous preferences for academic quality, while column 4 models heterogeneous preferences for school neighborhood characteristics. The estimation sample for each column consists of applicants to grades 5 and 6—common middle school entry grades for DC schools.

* $p < .05$, ** $p < .01$, *** $p < .001$; --0-- no p-value, parameter is constrained to zero.

PMF is “Performance Management Framework,” which is used to rate charter schools.

Table. B.7. Alternate logit specifications: High school

School characteristics	Rank-ordered logit	Conditional logit	Mixed logit (1)	Mixed logit (2)
CONVENIENCE				
Distance (miles)	-0.021**	-0.058***	-0.061***	-0.058***
On at least two bus lines	0.043	0.708***	0.731***	0.704***
On subway	0.136*	0.009	-0.002	0.009
SCHOOL DEMOGRAPHICS				
Own-race percentage/10	0.172***	0.197**	0.232**	0.197**
Own-race percentage/10 squared	-0.010**	-0.007	-0.010	-0.007
Percentage low income (direct-certified)/10	0.038	0.010	0.040	0.010
ACADEMICS—PROFICIENCY AND GROWTH				
Proficiency rate/10	0.143***	0.250***	0.269***	0.250***
[Random coefficient std. dev.]			[0.034]	
Median growth percentile/10 (math)	-0.196***	-0.247***	-0.276***	-0.242***
[Random coefficient std. dev.]			[0.105]	
ACADEMICS—CHARTER SCHOOL ACCOUNTABILITY RATING				
PMF Tier 1 (charters only)	-0.292*	-0.253	-0.209	-0.193
[Random coefficient std. dev.]			[0.416]	
PMF Tier 2 (charters only)	-0.019	0.628*	0.702*	0.684*
[Random coefficient std. dev.]			[0.343]	
PMF Tier 3 (charter only) - omitted category	--0--	--0--	--0--	--0--
ACADEMICS—STATE ACCOUNTABILITY RATING				
Reward	1.204***	1.636***	1.844***	1.695***
[Random coefficient std. dev.]			[0.852]**	
Rising	0.541***	0.852***	0.939***	0.896***
[Random coefficient std. dev.]			[0.709]	
Developing	0.296*	0.111	0.199	0.167
[Random coefficient std. dev.]			[0.069]	
Priority - omitted category	--0--	--0--	--0--	--0--
Focus	0.114	0.242	0.056	0.227
[Random coefficient std. dev.]			[1.307]**	
SCHOOL NEIGHBORHOOD				
Crime rate, violent crimes/month	0.283*	1.053***	1.074***	1.053***
[Random coefficient std. dev.]				[0.019]
Crime rate, property crimes/month	-0.141***	-0.373***	-0.397***	-0.373***
[Random coefficient std. dev.]				[0.023]
Log (household income)	0.098	0.548***	0.619***	0.547***
[Random coefficient std. dev.]				[0.001]
OTHER SCHOOL ATTRIBUTES (TRADITIONAL SCHOOLS ONLY)				
Average core class size (number of students)	-0.007	-0.063**	-0.065*	-0.063**
Requires school uniforms	-0.010	-0.363	-0.392	-0.363
Has after-school programs	0.086	0.327	0.373	0.327
Sample size (student-school combinations)	**11,543**	**10,930**	**10,930**	**10,930**

Notes: Estimates presented are generated from rank-ordered logit (column 1), conditional logit (column 2), and mixed-logit (columns 3 and 4) specifications. Column 3 is a mixed-logit model of heterogeneous preferences for academic quality, while column 4 models heterogeneous preferences for school neighborhood characteristics. The estimation sample for each column consists of applicants to grade 9—the common high school entry grade for DC schools.

* $p < .05$, ** $p < .01$, *** $p < .001$, no p-value, parameter is constrained to zero.

PMF is "Performance Management Framework," which is used to rate charter schools.

For elementary and middle school, we find there is little heterogeneity in the preference for schools meeting the highest state accountability rating category, with a statistically insignificant estimate of roughly 0.2 for each of the random coefficient standard deviations. The estimated standard deviation of the coefficients for the lower-rated categories, however, are significant and much larger for elementary, while also larger for the next-lowest category at the middle school level. Combined with the larger coefficient mean on the highest accountability category, this suggests that applicants as a whole more consistently choose schools from the highest category, while there is much more varied demand for schools in the lower categories. Estimates for the charter school accountability rating categories are also consistent with this behavior, as the estimated distribution of the Tier 2 coefficient is roughly 10 times wider than that of the higher Tier 1 rating. The analogous results in Table B.7 suggest there is relatively less heterogeneity in preferences for academic quality among applicants entering high school.

Looking at proficiency rates, there is little heterogeneity at the middle and high school levels. However, the proficiency rate coefficient for elementary has a mean of 0.11 and a standard deviation of roughly 0.19, suggesting there is considerably more heterogeneity in the preference for schools with high proficiency rates among applicants for elementary entry grades. This is consistent with the fact that some schools in the choice sets of these grade levels only serve lower, untested grade levels and do not receive standardized testing proficiency rates. Moreover, it may be that parents place a lower value on schools' academic achievement rates than other attributes until their children are closer to entering a tested grade level.

APPENDIX C. SUPPLEMENTAL TABLES AND FIGURES

Table. C.1. Alternative measures of academic quality: Elementary entry grades (pre-K and K)

School characteristics	Proficiency rate		Median growth percentile		Charter tier		ESEA classification		Proficiency and ESEA classification		Charter tier and ESEA classificatio n	
CONVENIENCE												
Distance (miles)	-0.09	***	-0.09	***	-0.08	***	-0.09	***	-0.09	***	-0.09	***
On at least two bus lines	0.10	***	0.13	***	0.12	***	0.13	***	0.10	***	0.13	***
On subway	0.10	***	0.13	***	0.12	***	0.13	***	0.11	***	0.14	***
SCHOOL DEMOGRAPHICS												
Own-race percentage/10	0.06	***	0.06	***	0.06	***	0.07	***	-0.09	***	-0.09	***
Own-race percentage/10 squared	0.00		0.00		0.00		0.00	*	0.10	***	0.13	***
Percentage low income (direct-certified)/10	-0.16	***	-0.20	***	-0.19	***	-0.19	***	0.11	***	0.14	***
ACADEMICS—PROFICIENCY AND GROWTH												
Proficiency rate/10	0.09	***							0.09	***		
Median growth percentile/10 (math)			0.03	***								
ACADEMICS—CHARTER SCHOOL ACCOUNTABILITY RATING												
PMF Tier 1 (charters only)					0.22	***					0.18	***
PMF Tier 2 (charters only)					0.06						0.03	
PMF Tier 3 (charter only) - omitted category					--0--						--0--	
ACADEMICS—STATE ACCOUNTABILITY RATING												
Reward							0.34	***	0.05		0.33	***
Rising							0.15	***	-0.03		0.13	***
Developing							0.03		0.00		0.06	
Priority - omitted category							--0--		--0--		--0--	
Focus							0.05		0.00		0.06	
Sample size (student-school combinations)	**51,572**		**51,572**		**51,572**		**51,572**		**51,572**		**51,572**	

Notes: * $p < .05$, ** $p < .01$, *** $p < .001$; --0-- no *p*-value, parameter is constrained to zero. PMF is "Performance Management Framework," which is used to rate charter schools. ESEA is the Elementary and Secondary Education Act, for which schools receive an accountability index score. These scores are used to classify schools in the discrete categories used in the relevant regression specifications.

Model includes school neighborhood and other school attributes, but coefficients not shown.

Entry grades for elementary school are pre-kindergarten (ages 3 and 4) and kindergarten.

Table. C.2. Alternative measures of academic quality: Middle school entry grades (5 and 6)

School characteristics	Proficiency rate	Median growth percentile	Charter tier	ESEA classification	Proficiency and ESEA classification	Charter tier and ESEA classification
CONVENIENCE						
Distance (miles)	-0.06 ***	-0.06 ***	-0.05 ***	-0.06 ***	-0.06 ***	-0.05 ***
On at least two bus lines	0.12 **	0.25 ***	0.18 ***	0.23 ***	0.18 ***	0.21 ***
On subway	0.10 *	0.05	0.10 *	0.04	0.09 *	0.07
SCHOOL DEMOGRAPHICS						
Own-race percentage/10	0.10 ***	0.06 *	0.06	0.16 ***	0.17 ***	0.15 ***
Own-race percentage/10 squared	-0.01 ***	-0.01 *	-0.01 *	-0.02 ***	-0.02 ***	-0.02 ***
Percentage low income (direct-certified)/10	0.06 *	-0.04	-0.01	0.06 **	0.10 ***	0.08 **
ACADEMICS—PROFICIENCY AND GROWTH						
Proficiency rate/10	0.11 ***				0.06 **	
Median growth percentile/10 (math)		-0.03 *				
ACADEMICS—CHARTER SCHOOL ACCOUNTABILITY RATING						
PMF Tier 1 (charters only)			0.36 ***			0.23 **
PMF Tier 2 (charters only)			0.21 *			0.12
PMF Tier 3 (charter only) - omitted category			--0--			--0--
ACADEMICS—STATE ACCOUNTABILITY RATING						
Reward				0.52 ***	0.32 *	0.49 ***
Rising				0.18	0.05	0.18
Developing				0.29 *	0.15	0.30 *
Priority - omitted category				--0--	--0--	--0--
Focus				-0.25 *	-0.32 *	-0.24
Sample size (student-school combinations)	**9,045**	**9,045**	**9,045**	**9,045**	**9,045**	**9,045**

Notes: * *p* < .05, ** *p* < .01, *** *p* < .001; --0-- no *p*-value, parameter is constrained to zero. PMF is "Performance Management Framework," which is used to rate charter schools. ESEA is the Elementary and Secondary Education Act, for which schools receive an accountability index score. These scores are used to classify schools in the discrete categories used in the relevant regression specifications.

Model includes school neighborhood and other school attributes, but coefficients suppressed.

Entry grades for middle school include 5 and 6.

Table. C.3. Alternative measures of academic quality: High school entry grade (9)

School characteristics	Proficiency rate		Median growth percentile		Charter tier		ESEA classification		Proficiency and ESEA classification		Charter tier and ESEA classification	
CONVENIENCE												
Distance (miles)	-0.03	***	-0.04	***	-0.05	***	-0.02	**	-0.02	**	-0.02	**
On at least two bus lines	-0.06		0.15	**	0.12	*	0.11	*	0.06		0.24	***
On subway	0.15	***	0.01		0.01		0.23	***	0.22	***	0.15	**
SCHOOL DEMOGRAPHICS												
Own-race percentage/10	0.20	***	0.18	***	0.09	*	0.19	***	0.20	***	0.15	***
Own-race percentage/10 squared	-0.01	***	-0.01	***	0.00		-0.01	***	-0.01	***	-0.01	*
Percentage low income (direct-certified)/10	0.01		-0.14	***	-0.41	***	0.14	**	0.16	***	0.07	
ACADEMICS—PROFICIENCY AND GROWTH												
Proficiency rate/10	0.18	***							0.06	***		
Median growth percentile/10 (math)			0.14	***								
ACADEMICS—CHARTER SCHOOL ACCOUNTABILITY RATING												
PMF Tier 1 (charters only)					-0.16						0.03	
PMF Tier 2 (charters only)					-0.01						0.29	**
PMF Tier 3 (charter only) - omitted category					--0--						--0--	
ACADEMICS—STATE ACCOUNTABILITY RATING												
Reward							1.23	***	0.92	***	1.20	***
Rising							0.81	***	0.57	***	0.79	***
Developing							0.86	***	0.77	***	0.63	***
Priority - omitted category							--0--		--0--		--0--	
Focus							0.09		0.03		-0.02	
Sample size (student-school combinations)	**11,543**		**11,543**		**11,543**		**11,543**		**11,543**		**11,543**	

Notes: * $p < .05$, ** $p < .01$, *** $p < .001$, no p-value, parameter is constrained to zero. PMF is "Performance Management Framework," which is used to rate charter schools. ESEA is the Elementary and Secondary Education Act, for which schools receive an accountability index score. These scores are used to classify schools in the discrete categories used in the relevant regression specifications.

Model includes school neighborhood and other school attributes, but coefficients suppressed.

The entry grade for high school is 9.

Table. C.4. Rank-ordered logit, benchmark model results

School Characteristics	Applicants Entering… Elementary School		Middle School		High School	
CONVENIENCE						
Distance (miles)	-0.094	***	-0.057	***	-0.021	**
	(0.004)		(0.008)		(0.006)	
On at least two bus lines	0.098	***	0.225	***	0.043	
	(0.020)		(0.047)		(0.069)	
On subway	0.113	***	0.063		0.136	*
	(0.018)		(0.049)		(0.059)	
SCHOOL DEMOGRAPHICS						
Own-race percentage/10	0.061	***	0.163	***	0.172	***
	(0.011)		(0.033)		(0.038)	
Own-race percentage/10 squared	-0.002		-0.016	***	-0.01	**
	(0.001)		(0.003)		(0.003)	
Percentage low income (direct-certified)/10	-0.161	***	0.149	***	0.038	
	(0.010)		(0.031)		(0.054)	
SCHOOL NEIGHBORHOOD						
Crime rate, violent crimes/month	0.23	***	-0.088		0.283	**
	(0.022)		(0.066)		(0.109)	
Crime rate, property crimes/month	-0.045	***	-0.001		-0.141	***
	(0.006)		(0.017)		(0.032)	
Log (household income)	-0.062	***	0.082		0.098	
	(0.017)		(0.043)		(0.052)	
ACADEMICS -- PROFICIENCY AND GROWTH						
Proficiency rate/10	0.085	***	0.07	**	0.143	***
	(0.008)		(0.026)		(0.023)	
Median growth percentile/10 (math)	-0.008		-0.111	***	-0.196	***
	(0.007)		(0.018)		(0.030)	
ACADEMICS - CHARTER SCHOOL ACCOUNTABILITY RATING						
PMF Tier 1 (charters only)	0.101		0.228		-0.292	*
	(0.052)		(0.123)		(0.125)	
PMF Tier 2 (charters only)	-0.003		0.028		-0.019	
	(0.046)		(0.108)		(0.113)	
PMF Tier 3 (charter only) - omitted category	--0--		--0--		--0--	
ACADEMICS - STATE ACCOUNTABILITY RATING						
Reward	0.061		0.383	**	1.204	***
	(0.049)		(0.136)		(0.164)	
Rising	-0.028		0.121		0.541	***
	(0.040)		(0.119)		(0.110)	
Developing	0.011		0.138		0.296	*
	(0.044)		(0.130)		(0.130)	
Priority - omitted category	--0--		--0--		--0--	
Focus	0.007		-0.262	*	0.114	
	(0.039)		(0.130)		(0.089)	

School Characteristics	Applicants Entering… Elementary School		Middle School		High School
OTHER SCHOOL ATTRIBUTES (TRADITIONAL SCHOOLS ONLY)					
Average core class size (number of students)	0.018	***	0.027	*	-0.007
	(0.004)		(0.011)		(0.012)
Requires school uniforms	-0.307	***	0.065		-0.01
	(0.028)		(0.086)		(0.094)
Has before-care	0.139	***	-0.132		(omitted)
	(0.025)		(0.070)		
Has after-school programs	-0.085	**	-0.079		0.086
	(0.026)		(0.069)		(0.081)
Sample size (student-school combinations)	**51,572**		**9,045**		**11,543**

Notes: * $p < .05$, ** $p < .01$, *** $p < .001$; --0-- no p-value, parameter is constrained to zero. Standard errors in parentheses. Variables with "/10" can be interpreted as one unit representing 10 percentage points.

PMF is "Performance Management Framework," which is used to rate charter schools.

Sample for each column is applicants to entry grades for the respective school level: Pre-K and kindergarten for elementary, grades 5 and 6 for middle school, and grade 9 for high school.

Table. C.5. Model parameters interacted with low-income status

School Characteristics	Elementary School Main Effect	Elementary School Interaction	Middle School Main Effect	Middle School Interaction	High School Main Effect	High School Interaction
CONVENIENCE						
Distance (miles)	-0.107 ***	0.037 ***	-0.042 ***	-0.032	-0.014	-0.017
	(0.005)	(0.008)	(0.010)	(0.017)	(0.009)	(0.013)
On at least two bus lines	0.083 ***	0.038	0.298 ***	-0.179	0.073	-0.084
	(0.024)	(0.042)	(0.063)	(0.093)	(0.092)	(0.128)
On subway	0.132 ***	-0.019	0.020	0.080	0.173 *	-0.113
	(0.021)	(0.039)	(0.064)	(0.098)	(0.079)	(0.113)
SCHOOL DEMOGRAPHICS						
Own-race percentage/10	0.070 ***	-0.059 *	0.189 ***	-0.064	0.142 **	0.117
	(0.013)	(0.028)	(0.042)	(0.069)	(0.047)	(0.081)
Own-race percentage/10 squared	-0.002	0.003	-0.019 ***	0.007	-0.007	-0.011
	(0.001)	(0.003)	(0.004)	(0.007)	(0.004)	(0.007)
Percentage low income (direct-certified)/10	-0.218 ***	0.190 ***	0.159 ***	0.001	0.033	0.045
	(0.012)	(0.022)	(0.041)	(0.062)	(0.070)	(0.107)
SCHOOL NEIGHBORHOOD						
Crime rate, violent crimes/month	0.280 ***	-0.143 **	-0.220 *	0.266 *	0.139	0.325
	(0.027)	(0.048)	(0.090)	(0.120)	(0.143)	(0.197)
Crime rate, property crimes/month	-0.054 ***	0.017	0.028	-0.058	-0.122 **	-0.049
	(0.007)	(0.015)	(0.021)	(0.031)	(0.044)	(0.057)
Log (household income)	-0.088 ***	0.090 *	0.067	0.056	0.052	0.081
	(0.022)	(0.038)	(0.057)	(0.087)	(0.070)	(0.090)
ACADEMICS -- PROFICIENCY AND GROWTH						
Proficiency rate/10	0.088 ***	-0.007	0.029	0.107 *	0.130 ***	0.039
	(0.010)	(0.015)	(0.033)	(0.046)	(0.033)	(0.043)
Median growth percentile/10 (math)	-0.007	-0.006	-0.091 ***	-0.026	-0.189 ***	-0.011
	(0.007)	(0.010)	(0.022)	(0.027)	(0.034)	(0.032)
ACADEMICS - CHARTER SCHOOL ACCOUNTABILITY RATING						
PMF Tier 1 (charters only)	0.105	-0.015	0.378 *	-0.305	-0.168	-0.316
	(0.059)	(0.090)	(0.153)	(0.175)	(0.173)	(0.244)
PMF Tier 2 (charters only)	-0.005	-0.031	0.131	-0.148	0.001	-0.078
	(0.052)	(0.061)	(0.135)	(0.151)	(0.148)	(0.177)
PMF Tier 3 (charter only) - omitted category	--0--	--0--	--0--	--0--	--0--	--0--

School Characteristics	Elementary School Main Effect	Elementary School Interaction	Middle School Main Effect	Middle School Interaction	High School Main Effect	High School Interaction
ACADEMICS - STATE ACCOUNTABILITY RATING						
Reward	0.066	0.027	0.811 ***	-0.920 ***	1.405 ***	-0.431
	(0.063)	(0.109)	(0.186)	(0.240)	(0.215)	(0.262)
Rising	-0.004	-0.017	0.378 *	-0.511 *	0.708 ***	-0.322
	(0.053)	(0.084)	(0.163)	(0.209)	(0.155)	(0.199)
Developing	-0.003	0.038	0.235	-0.233	0.600 **	-0.580 *
	(0.060)	(0.084)	(0.177)	(0.217)	(0.183)	(0.249)
Priority - omitted category	--0--	--0--	--0--	--0--	--0--	--0--
Focus	0.064	-0.109	-0.130	-0.221	0.219	-0.152
	(0.049)	(0.070)	(0.182)	(0.241)	(0.119)	(0.160)
OTHER SCHOOL ATTRIBUTES (TRADITIONAL SCHOOLS ONLY)						
Average core class size (number of students)	0.020 ***	-0.007	0.026 *	0.000	0.005	-0.024
	(0.004)	(0.004)	(0.012)	(0.011)	(0.015)	(0.018)
Requires school uniforms	-0.312 ***	0.071	0.163	-0.222	-0.129	0.282
	(0.031)	(0.062)	(0.098)	(0.143)	(0.127)	(0.177)
Has before-care	0.143 ***	0.031	-0.055	-0.123	(omitted)	(omitted)
	(0.031)	(0.058)	(0.093)	(0.143)	0.000	0.000
Has after-school programs	-0.098 **	0.021	-0.163	0.210	0.166	-0.182
	(0.032)	(0.059)	(0.093)	(0.138)	(0.112)	(0.150)
Sample size (student-school combinations)	**51,572**		**9,045**		**11,543**	

Notes: * *p* < .05, ** *p* < .01, *** *p* < .001, --0-- no *p*-value, parameter is constrained to zero. Standard errors in parentheses.

For each school level, main effect and interaction columns report coefficient estimates from the same regression. Coefficients reported in the interacted columns are those for the listed school characteristic interacted with the student's direct certification status for free school meals. Because the coefficients reported in the main effects columns correspond to the overall association among all students, the sum of the main and interacted coefficients should be interpreted as the association between school characteristics and preferences for schools for direct-certified students.

PMF is "Performance Management Framework," which is used to rate charter schools. Sample for each column is applicants to entry grades for the respective school level: Pre-K and kindergarten for elementary, grades 5 and 6 for middle school, and grade 9 for high school.

Model includes school neighborhood and other school attributes, but coefficients not shown.

Entry grades are pre-K and kindergarten for elementary, grades 5 and 6 for middle school, and grade 9 for high school.

Table. C.6. Race/ethnicity interactions

School Characteristics	Elementary			Middle			High		
	Black	White	Hispanic	Black	White	Hispanic	Black	White	Hispanic
CONVENIENCE									
Distance (miles)	-0.075 ***	-0.208 ***	-0.079 ***	-0.064 ***	-0.017	-0.047	-0.022 **	-0.004	-0.031
	(0.004)	(0.011)	(0.014)	(0.009)	(0.035)	(0.029)	(0.007)	(0.083)	(0.024)
On at least two bus lines	0.086 ***	0.039	-0.031	0.165 **	1.610 ***	0.006	0.005	-0.931	0.345
	(0.023)	(0.051)	(0.071)	(0.053)	(0.254)	(0.171)	(0.081)	(1.094)	(0.261)
On subway	0.121 ***	0.148 ***	0.220 ***	0.016	0.310	0.235	0.136	1.834 *	0.233
	(0.023)	(0.039)	(0.057)	(0.054)	(0.264)	(0.161)	(0.080)	(0.754)	(0.216)
SCHOOL DEMOGRAPHICS									
Own-race percentage/10	-0.013	0.109 ***	0.047	0.188 ***	0.178	0.040	0.294	-0.169	0.485 *
	(0.015)	(0.031)	(0.037)	(0.051)	(0.189)	(0.123)	(0.158)	(0.390)	(0.195)
Own-race percentage/10 squared	0.001	-0.009 *	0.003	-0.020 ***	-0.034	-0.004	-0.019	0.003	-0.064 *
	(0.001)	(0.004)	(0.004)	(0.004)	(0.022)	(0.016)	(0.012)	(0.087)	(0.032)
Percentage low income (direct-certified)/10	-0.062 ***	-0.438 ***	-0.161 ***	0.214 ***	-0.110	-0.037	0.072	-0.033	0.182
	(0.013)	(0.028)	(0.030)	(0.035)	(0.153)	(0.093)	(0.074)	(0.604)	(0.171)
SCHOOL NEIGHBORHOOD									
Crime rate, violent crimes/month	0.175 ***	0.366 ***	0.252 **	-0.050	-0.261	-0.263	0.394 ***	-0.917	0.107
	(0.027)	(0.054)	(0.092)	(0.071)	(0.382)	(0.256)	(0.118)	(1.748)	(0.370)
Crime rate, property crimes/month	-0.037 ***	-0.093 ***	-0.067 **	-0.024	0.099	0.073	-0.155 ***	-0.450	-0.077
	(0.008)	(0.013)	(0.024)	(0.019)	(0.082)	(0.060)	(0.034)	(0.743)	(0.126)
Log (household income)	-0.002	-0.155 **	-0.078	0.132 **	0.259	-0.037	0.127 *	-0.803	-0.126
	(0.021)	(0.048)	(0.068)	(0.047)	(0.236)	(0.156)	(0.058)	(1.058)	(0.191)
ACADEMICS -- PROFICIENCY AND GROWTH									
Proficiency rate/10	0.095 ***	0.106 ***	0.057 *	0.089 **	0.144	-0.053	0.150 ***	-0.215	0.192 *
	(0.010)	(0.021)	(0.026)	(0.030)	(0.124)	(0.095)	(0.024)	(0.408)	(0.086)
Median growth percentile/10 (math)	-0.022 **	0.016	-0.021	-0.093 ***	-0.251 ***	-0.125 *	-0.222 ***	-0.248	-0.203 **
	(0.008)	(0.012)	(0.016)	(0.020)	(0.066)	(0.056)	(0.040)	(0.275)	(0.068)
ACADEMICS - CHARTER SCHOOL ACCOUNTABILITY RATING									
PMF Tier 1 (charters only)	-0.009	0.190	0.345 *	0.184	2.122 ***	0.598	-0.333 *	-0.438	-0.044
	(0.059)	(0.108)	(0.150)	(0.131)	(0.624)	(0.468)	(0.134)	(2.495)	(0.466)
PMF Tier 2 (charters only)	-0.039	-0.039	0.056	-0.053	0.538	0.644	-0.125	-1.669	0.222
	(0.048)	(0.099)	(0.120)	(0.112)	(0.580)	(0.424)	(0.141)	(2.778)	(0.401)
PMF Tier 3 (charter only) - omitted category	--0--	--0--	--0--	--0--	--0--		--0--	--0--	--0--

School Characteristics	Elementary			Middle			High		
	Black	White	Hispanic	Black	White	Hispanic	Black	White	Hispanic
ACADEMICS - STATE ACCOUNTABILITY RATING									
Reward	0.024	0.021	0.311	0.340 *	-0.066	0.627	1.263 ***	5.257 *	1.416 *
	(0.058)	(0.160)	(0.197)	(0.145)	(0.875)	(0.518)	(0.203)	(2.434)	(0.627)
Rising	-0.067	0.050	0.188	0.128	-0.213	0.385	0.589 ***	3.338 *	0.882
	(0.045)	(0.138)	(0.161)	(0.128)	(0.793)	(0.399)	(0.145)	(1.675)	(0.462)
Developing	-0.010	-0.266	0.434 *	0.134	0.908	0.001	0.270	1.611	1.198 *
	(0.046)	(0.252)	(0.221)	(0.138)	(1.194)	(0.451)	(0.165)	(2.034)	(0.492)
Priority - omitted category	--0--	--0--	--0--	--0--	--0--	--0--	--0--	--0--	--0--
Focus	-0.034	0.158	0.331 *	-0.211	0.258	-0.104	0.230	1.316	0.331
	(0.042)	(0.120)	(0.146)	(0.140)	(1.022)	(0.418)	(0.131)	(1.755)	(0.343)
OTHER SCHOOL ATTRIBUTES (TRADITIONAL SCHOOLS ONLY)									
Average core class size (number of students)	0.017 ***	0.020 ***	0.027 ***	0.025 *	0.086 **	0.071 **	-0.004	0.119	0.007
	(0.004)	(0.006)	(0.007)	(0.011)	(0.031)	(0.027)	(0.016)	(0.202)	(0.036)
Requires school uniforms	-0.195 ***	-0.390 ***	-0.192 *	0.089	-0.110	-0.153	0.033	-0.028	0.146
	(0.038)	(0.055)	(0.076)	(0.107)	(0.273)	(0.250)	(0.107)	(1.834)	(0.296)
Has before-care	0.175 ***	0.147 *	0.100	-0.095	-0.181	-0.260	(omitted)	(omitted)	(omitted)
	(0.031)	(0.062)	(0.074)	(0.078)	(0.363)	(0.232)			
Has after-school programs	-0.113 ***	-0.026	-0.188 **	-0.055	-0.248	-0.051	0.132	-0.564	0.048
	(0.033)	(0.062)	(0.071)	(0.079)	(0.357)	(0.187)	(0.087)	(1.436)	(0.262)
Sample size (student-school combinations)		**51,572**			**9,045**			**11,543**	

Notes: * $p < .05$, ** $p < .01$, *** $p < .001$; --0-- no p-value, parameter is constrained to zero. Standard errors in parentheses.

PMF is "Performance Management Framework," which is used to rate charter schools. Sample for each column is applicants to entry grades for the respective school level who identify as the corresponding race category.

Model includes school neighborhood and other school attributes, dummies for missing values, but coefficients not shown. See Appendix A for detailed set of covariates.

Entry grades are pre-K and kindergarten for elementary, grades 5 and 6 for middle school, and grade 9 for high school.

Table. C.7. Alternative Distance Models

	(1)		(2)		(3)		(4)		(5)	
On at least two bus lines	0.098	***	0.102	***	0.1	***	0.098	***	0.109	***
	(0.020)		(0.020)		(0.020)		(0.020)		(0.020)	
On subway	0.113	***	0.133	***	0.142	***	0.113	***	0.114	***
	(0.018)		(0.018)		(0.018)		(0.018)		(0.018)	
Distance, right-angle	-0.094	***	-0.177	***						
	(0.004)		(0.009)							
Distance squared, right-angle			0.01	***						
			(0.001)							
Distance, if less than 1 mile					-0.688	***				
					(0.050)					
Distance if greater than 1 mile					-0.068	***				
					(0.004)					
Distance is greater than 1 mile (dummy)					-0.601	***				
					(0.035)					
Distance, straight line							-0.124	***		
							(0.005)			
Route distance from mapping software									-0.104	***
									(0.004)	
Route time from mapping software (minutes)										
Sample size (student-school combinations)	**51,572**		**51,572**		**51,572**		**51,572**		**51,572**	

Notes: * $p < .05$, ** $p < .01$, *** $p < .001$; --0-- no *p*-value, parameter is constrained to zero. Standard errors in parentheses. Variables other than distance included in the model, but omitted from table for brevity

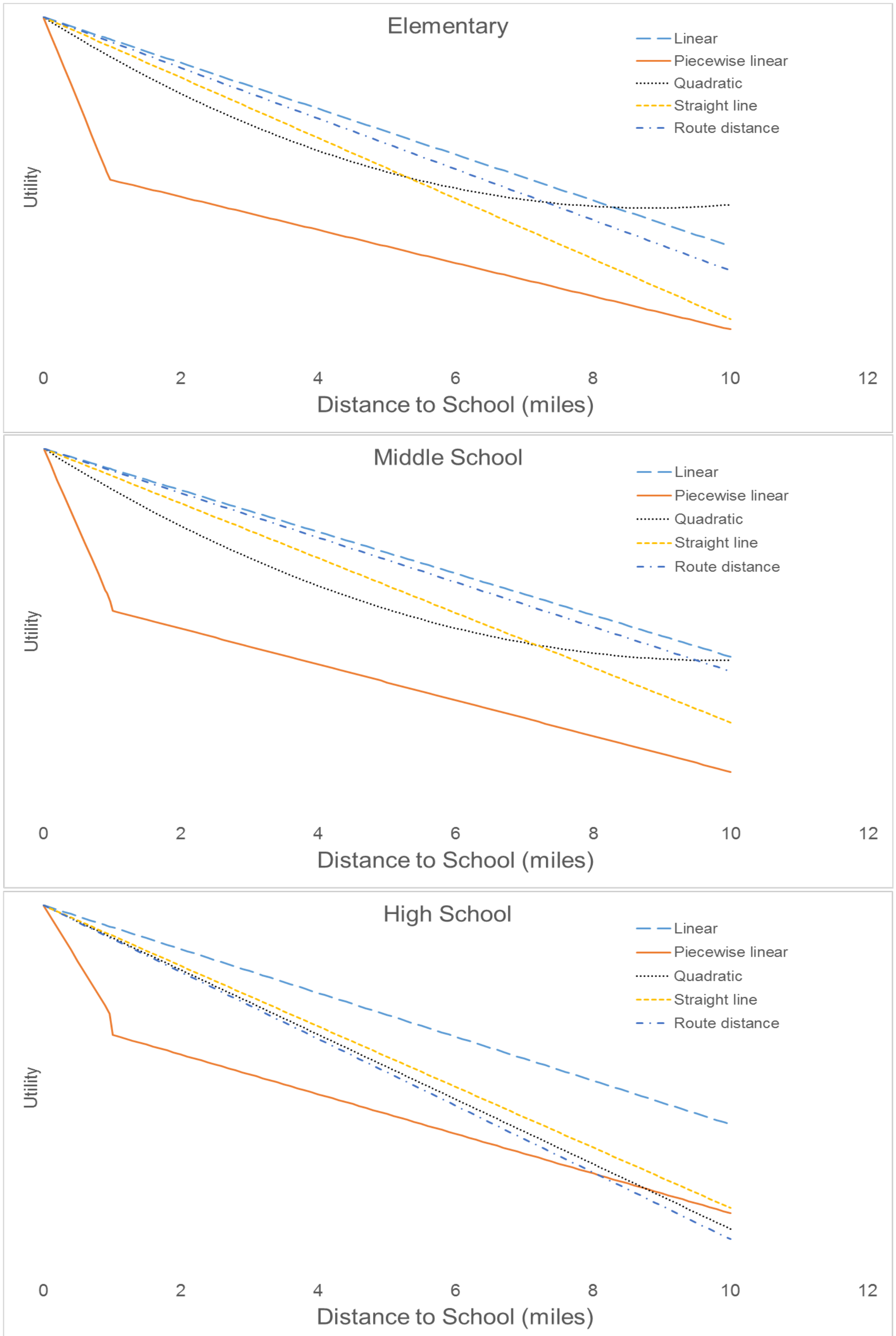
Table. C.8. Role of academic indicators, alternative specifications

	Benchmark (categorical)		Continuous		Continuous and Categorical	
Elementary						
ACADEMICS -- PROFICIENCY AND GROWTH						
Proficiency rate/10	0.085	***	0.052	*	0.077	**
	(0.008)		(0.023)		(0.024)	
Median growth percentile/10 (math)	-0.008		-0.013		-0.005	
	(0.007)		(0.007)		(0.007)	
ACADEMICS - CHARTER SCHOOL ACCOUNTABILITY RATING						
PMF Tier 1 (charters only)	0.101				0.316	***
	(0.052)				(0.091)	
PMF Tier 2 (charters only)	-0.003				0.106	
	(0.046)				(0.060)	
PMF Tier 3 (charter only) - omitted	--0--				--0--	
PMF Accountability index/10			0.000		-0.061	**
			(0.011)		(0.021)	
ACADEMICS - STATE ACCOUNTABILITY RATING						
Reward	0.061				0.048	
	(0.049)				(0.049)	
Rising	-0.028				-0.037	
	(0.040)				(0.040)	
Developing	0.011				0.000	
	(0.044)				(0.045)	
Priority (omitted)	--0--				--0--	
Focus	0.007				0.005	
	(0.039)				(0.039)	
Accountability index/10			0.042		0.015	
			(0.025)		(0.026)	
N (student-school combinations)	51,572		51,572		51,572	
Middle School						
ACADEMICS -- PROFICIENCY AND GROWTH						
Proficiency rate/10	0.070	**	-0.380	***	-0.287	**
	(0.026)		(0.099)		(0.101)	
Median growth percentile/10 (math)	-0.111	***	-0.118	***	-0.121	***
	(0.018)		(0.020)		(0.021)	
ACADEMICS - CHARTER SCHOOL ACCOUNTABILITY RATING						
PMF Tier 1 (charters only)	0.228				0.142	
	(0.123)				(0.171)	
PMF Tier 2 (charters only)	0.028				-0.023	
	(0.108)				(0.123)	
PMF Tier 3 (charter only) - omitted	--0--				--0--	
PMF Accountability index/10			0.024		0.02	
			(0.026)		(0.040)	
ACADEMICS - STATE ACCOUNTABILITY RATING						
Reward	0.383	**			0.313	*
	(0.136)				(0.139)	
Rising	0.121				0.109	

	Benchmark (categorical)		Continuous		Continuous and Categorical	
	(0.119)				(0.121)	
Developing	0.138				0.177	
	(0.130)				(0.131)	
Priority (omitted)	--0--				--0--	
Focus	-0.262	*			-0.228	
	(0.130)				(0.131)	
Accountability index/10			0.532	***	0.372	***
			(0.097)		(0.105)	
N (student-school combinations)	9,045		9,045		9,045	
High School						
ACADEMICS -- PROFICIENCY AND GROWTH						
Proficiency rate/10	0.143	***	0.435	***	0.578	***
	(0.023)		(0.073)		(0.138)	
Median growth percentile/10 (math)	-0.196	***	-0.023		-0.095	
	(0.030)		(0.019)		(0.056)	
ACADEMICS - CHARTER SCHOOL ACCOUNTABILITY RATING						
PMF Tier 1 (charters only)	-0.292	*			1.035	**
	(0.125)				(0.330)	
PMF Tier 2 (charters only)	-0.019				0.745	*
	(0.113)				(0.305)	
PMF Tier 3 (charter only) - omitted	--0--				--0--	
PMF Accountability index/10			-0.149	***	-0.252	***
			(0.020)		(0.067)	
ACADEMICS - STATE ACCOUNTABILITY RATING						
Reward	1.204	***			1.390	***
	(0.164)				(0.239)	
Rising	0.541	***			0.711	***
	(0.110)				(0.128)	
Developing	0.296	*			0.175	
	(0.130)				(0.146)	
Priority (omitted)	--0--				--0--	
Focus	0.114				-0.167	
	(0.089)				(0.160)	
Accountability index/10			-0.242	**	-0.596	***
			(0.082)		(0.166)	
N (student-school combinations)	11,543		11,543		11,543	

Notes: * *p* < .05, ** *p* < .01, *** *p* < .001; --0-- no p-value, parameter is constrained to zero. Standard errors in parentheses. Nonacademic variables included in model, not shown. The estimation sample for each panel consists of applicants to entry grades for the respective school level: Pre-K and kindergarten for elementary, grades 5 and 6 for middle school, and grade 9 for high school.

Figure C.1. Alternative distance models



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