Effects of Non-Academic Information on School Choice: Evidence from NYC Families' School Rankings*

Rene Crespin† Chantal Hailey‡

September 2026

Abstract

In this paper, we examine how publicizing non-academic school quality information—specifically, measures of student safety and satisfaction—affects families' high school preference rankings in New York City. Leveraging two plausibly exogenous information shocks, we find that families significantly increased their preference rankings for schools with higher safety and satisfaction ratings, without a change in preferences for schools' academic measures. Responses varied by family background, with lower-income students reacting more strongly to safety information. Importantly, we find that the format in which the information is delivered matters. Student safety is a school characteristic that parents value independent of how this information is delivered. However, families only value information about student satisfaction with course and extracurricular variety, when the information becomes salient and accessible in an interactive website. Our results suggest that non-academic school information can influence families' decisions, even in the absence of accountability policies.

*We would like to thank Sean Corcoran, Todd Elder, Scott Imberman, and Jennifer Jennings for helpful comments and discussions, as well as seminar participants at Michigan State University, Tufts University, and the Lab for Economic Opportunities at the University of Notre Dame. Madeleine Smith provided excellent research assistance. Data are provided by the New York City Department of Education through the Research Alliance for New York City Schools. This material is based upon work supported by The Policy Academies. All errors are our own.

†Michigan State University; crespin@msu.edu.

‡University of Texas - Austin; chantal.a.hailey@utexas.edu.

Introduction

As families increasingly make use of expanded school choice policies, such as open enrollment districts, charter schools, and public vouchers for private schools, understanding and communicating school quality has become critical. Since the Every Student Succeeds Act (ESSA) replaced No Child Left Behind (NCLB) in 2015, states and school districts across the US have shifted from relying solely on test-based measures of school quality to adopting more holistic approaches (Erwin et al., 2021). ESSA mandates that, in addition to reporting traditional measures of school performance, states must publicly provide information on other indicators of school quality and student success. For example, states may report metrics such as school climate or safety, factors that research shows may directly or indirectly impact students' short- and long-run outcomes (Angrist et al., 2025; Carrell & Hoekstra, 2010; Carrell et al., 2018; Porter et al., 2023).

Non-academic metrics of school quality are increasingly being used for public transparency (Cotman et al., 2024; Jordan & Hamilton, 2019). This growing publicity of non-traditional school metrics that were previously difficult to observe allows families to account for new characteristics in their school choice decision-making—potentially helping families better choose schools that produce what they value most (Friedman, 1962; Hoxby, 2003).

While much of academic research had previously focused on academic measures of school quality—such as test score levels and growth—there is growing research of how non-academic school characteristics, such as social environments, socioemotional development, and curricular satisfaction, may play a role in shaping families' school choices/preferences (Ainsworth et al., 2023; Beuermann et al., 2023; Hailey, 2025; Harris & Larsen, 2023). However, research on the value families place on non-academic school quality metrics or the impact of offering clear and consistent non-academic information to the public is limited.

In this paper, we provide causal evidence of how publicized non-academic measures of school quality affect families' school preferences, and how these preferences vary by student backgrounds. We leverage two plausibly exogenous shocks of information: one that revealed new non-academic information and another that increased the salience of non-academic and academic measures across NYC Public Schools in the mid-2010s.

Eighth grade NYC students are not automatically assigned to public neighborhood high schools. Instead, the NYC Department of Education (NYCDOE) requires all students to submit applications with their ranked list of schools and assigns students to schools based on these listed preferences. Prior to 2016, the district published large physical high school directory books that provided students with various measures of traditional school information. In 2016, the NYCDOE began including two non-academic metrics that will be the

focus of our analysis: (1) school-level measures of students' sense of safety and (2) students' satisfaction with course and extracurricular variety. Then in 2017, the district re-released all traditional and non-traditional measures of school quality in an online version of the directory. By providing the information in a concise way and without changing accountability policies that may affect other school characteristics, we are able to isolate families' preferences for non-academic measures of school quality.

We first show that schools' student safety and satisfaction provide information about dimensions of schools that are not captured by academic characteristics. Furthermore, we find that while schools' academics are highly predictable using traditionally-available school characteristics, non-academic characteristics are substantially less predictable.

Next, we infer families' preferences for school characteristics by examining their ranked lists of school choices. Using descriptive analysis, we provide a baseline of families' preferences for different school characteristics before the information shocks. Schools' academic levels have the strongest association with families' preferences. In terms of schools' non-academic characteristics, we find a strong, although weaker, association between families' preference rankings and measures of schools' safety and satisfaction. In heterogeneity analysis, higher achieving students have a substantially stronger association between their preference rankings and schools' safety, compared to lower-achieving students. However, we find that lower- and higher-income students have similar preferences for schools with better student safety measures. Lastly, we find that higher-achieving and higher-income families' preference rankings are more strongly associated with schools' student satisfaction and academic characteristics than that of their counterparts.

We then examine reactions to plausibly exogenous shocks of schools' non-academic information, through updating the physical High School Directories and starting an interactive online high school directory. These shocks of information provide unique opportunities to observe causal reactions in families' school rank ordering to new information that is not impacted by other intentional changes, such as school composition or accountability policies. We identify the effect of publicly releasing both traditional and non-traditional measures of school quality through event studies and a difference-in-differences framework.

Our event studies show flat relationships in families' preferences with academic and non-academic characteristics before the information shocks. Overall, we find that relative to the pre-shock period, for every 10-percentile higher student safety and for every 10-percentile higher student satisfaction, families' preference rankings for schools increased by about 0.14 and 0.12 percentile points, respectively, which are statistically significant at the 1% level. These estimated impacts correspond with 27% and 16% increases in families' preferences for school safety and satisfaction. These information effects are greater than what is found in

the literature in response to school value-added information shocks in Romania (Ainsworth et al., 2023) and in Los Angeles (Campos, 2024), but smaller than reactions to information about school test score levels in Mecklenburg, NC (Hastings & Weinstein, 2008).

We find variation in how different subgroups of families react to the information shocks. In general, lower-income students react more strongly to schools' safety information than their peers, while students exhibit similar reactions to information about schools' student satisfaction.

Importantly, our main results are robust to a series of alternative model specifications. We also find similar results when examining the impact of information on families' top-ranked school choices. For school choices that have the largest consequence for students' high school assignment, non-academic information shocks increased families' preferences for school safety and satisfaction by at least 25% and 11%, respectively.

Furthermore, we find that safety information in printed high school directories generated an immediate and sustained shift in preferences when this information is first released in 2016. However families only react to satisfaction measures when the information is delivered online through an interactive website.

We propose two potential mechanisms that help explain how non-academic school information shaped families' school choice preferences: (1) increased information salience and reduced search costs, and (2) the design and formatting of information in the directory. First, by including non-academic information in the printed directory and launching the online directory, the NYCDOE likely reduced the time and resources families previously spent searching for this information. As a result, families could more easily identify schools with higher levels of safety and academic quality, increasing demand for those schools. Supporting this mechanism, we find stronger responses to safety information among student subgroups that prior studies suggest face the greatest barriers to accessing such information. Further evidence of reduced search costs comes from the larger impacts of student satisfaction and academic information observed in 2018, which coincided with NYCDOE's increased promotion of the online directory and rising online search activity for the website in NYC.

Second, the structure of school performance data in the directory may help explain the delayed effect of student satisfaction information until 2018. The website's interactive search tool encouraged users to filter schools by extracurricular programs, themes, and courses, potentially prompting families to pay closer attention to the student satisfaction measure, which reflects how current students perceive schools' extracurricular and course offerings.

Relationship to the literature. We make several important contributions to three strands of research. First, we contribute to a growing literature examining whether and how much families value school characteristics beyond academic performance using revealed pref-

erence approaches.[1] This literature has focused on utilizing various proxies to infer families' preferences for non-academic-based school characteristics such as measures of student safety, happiness, or satisfaction; extracurriculars; or schools' causal impacts on crime, fertility, and labor market participation (Ainsworth et al., 2023; Beuermann et al., 2023; Burdick-Will et al., 2024; Gibbons & Silva, 2011; Hailey, 2025; Harris & Larsen, 2023; Jacob & Lefgren, 2007).[2] However, these studies must rely on selection on observables assumptions to estimate preferences. We contribute to this literature by examining reactions to a plausibly exogenous shock of new non-academic information.

This paper most directly contributes to research using information shocks to examine how families value non-academic school quality.[3] Crespin (2025) shows that families react positively to district-wide school social climate information in Chicago, leading to increases in sales prices for homes assigned to better climate schools. This information shock particularly attracted higher-income homebuyers. While Crespin (2025) relies on home price capitalization to proxy for families' preferences, we are able to directly examine how families' ranked lists of school applications change in response to the information shocks without relying on as large of investments as purchasing a home.

In concurrent work, Rachkovski (2025) examines how the initial release of information about schools' academics, satisfaction, and violence impacted Israeli families' middle school preferences, in a context where no prior public data infrastructure existed. In contrast, we explore the impacts of these types of novel data and increased information salience and accessibility within an already-established information infrastructure. This is critical, as all U.S. states and school districts currently maintain school data websites and report cards. As such, our study provides a more policy-relevant approximation of how improving access to existing school information could affect families' educational decisions.

Next, we contribute to a growing literature on the impacts of information on families' preferences for school academic quality. Generally, this literature finds mixed evidence of whether families value school academic impacts relative to school academic levels (Abdulkadiroğlu et al., 2020; Beuermann et al., 2023; Harris & Larsen, 2023). However, recent studies have shown that information is an important driver of differences in preferences for school

[1]Studies consistently show that parents self-report having strong preferences for better social conditions in schools (Gibbons & Silva, 2011; Goyette, 2014; Hassan & Geys, 2016; Idoux & Corradini, 2024); however, idealized perceptions and behavior may not necessarily manifest in real-life decisions through revealed preferences (Bruch & Mare, 2012; Gibbons & Silva, 2011; Parker & Souleles, 2017).

[2]Some of these preference proxies include families' ranked lists of schools, families' requests for specific teachers, or capitalization in the housing market.

[3]In a related literature, studies show that families have differential preferences for school racial and economic composition, using an information experiment with self-reported preferences (Billingham & Hunt, 2016; Hailey, 2022a), or using natural experiments with property sales price capitalization as a proxy for preferences (Clapp et al., 2008; Collins & Kaplan, 2022; Wada & Zahirovic-Herbert, 2013).

academic characteristics. Seminal work by Hastings and Weinstein (2008) used randomized experiments to show that providing families with information about schools' average test-scores has significant impacts on families' ranking of schools. Moreover, providing information about schools' test-based value-added has significant, although, smaller effects (Ainsworth et al., 2023; Campos, 2024). Our study contributes to this literature by examining the impacts of non-academic information shocks on families' ranking of schools.

Lastly, our paper contributes to a set of RCT-based studies of the impacts of providing school academic information through physical, app-based, or online forms of communication.[4] Relative to this literature, we study the impacts of improving accessibility of school academic information throughout a whole school district, without external accountability pressures.[5] This allows us to examine whether transitioning academic and non-academic information from physical to online format throughout NYC has comparable results to their experimental results with a smaller context. Additionally, past studies have been limited to examining differences in reactions to school academic performance information by students with or without free-lunch eligibility. However, in our study, we explore how context matters by examining heterogeneity by neighborhood socioeconomics.

Roadmap. This paper is organized as follows: Section 1 discusses the institutional background. Section 2 describes the data and sample. Section 3 examines whether school quality is multidimensional beyond academics, and Section 4 shows how families' preferences are associated with school features. Section 5 describes the empirical approach, Section 6 presents the main results, and Section 7 examines potential mechanisms. Section 8 concludes.

[4]More specifically, Cohodes et al. (2022) show that school-level randomized controlled trials that provide physical high school recommendation lists or introductions to app-based or online school choice tools reduce the likelihood that students will apply to high schools with low graduation rates. Similarly, Valant and Weixler (2022) demonstrate through a student-level RCT that providing families with school value-added accountability grades–delivered through flyers, email, and text messages–increased the likelihood of selecting high-growth schools. However, Corcoran et al. (2018) find that while directly providing lists to students of nearby high schools with above median graduation rates did not significantly lead students to apply to schools with higher graduation rates, it did reduce likelihoods of matching to low graduation rates schools.

[5]In a related line of research, studies have explored whether families' school preferences are impacted by school accountability ratings, which have external repercussions. Specifically, Rich and Jennings (2015) show that a school accountability shock in Chicago led families to transfer their children out of schools with worse academic ratings. Similarly, Corradini (2024) shows that the introduction of school accountability ratings in NYC attracted students towards better-rated schools and away from lower-rated schools.

1 Institutional Background

1.1 What are student safety and satisfaction, and do they matter?

Research and practice are not always aligned in what constitutes as valuable non-academic measures of school quality and how to measure them. One aspect of schools' non-academic characteristics emphasized by policy and in education research is school safety. In 2010, the US Department of Education incentivized states to develop rigorous measurement systems to assess the social conditions in their schools (Jennings, 2011). Through this process, the US Department of Education developed the *Safe and Supportive Schools* framework (U.S. Department of Education, 2013). This model focuses on three central components of school climate —safety, engagement, and environment (Cohen et al., 2008; Thapa et al., 2013).

School safety typically refers to students' protection from socioemotional and physical threats inside and around school buildings (Cornell et al., 2021; Edwards, 2021; Thapa et al., 2013). Correlational research shows that students with a stronger sense of school safety are more academically engaged and have better academic performance (Davis & Warner, 2018; Hamlin, 2021; Lacoe, 2020). Importantly, causal research shows that exposure to disruptive classmates can have negative effects on students' short- and long-run test scores, educational attainment, and earnings (Carrell & Hoekstra, 2010; Carrell et al., 2018).

Research suggests that families factor safety into their school selections. Controlling for other school characteristics, families avoid schools with more violence within and outside school walls (Burdick-Will et al., 2021; Denice & Gross, 2016). Moreover, NYC families are less likely to choose schools with more violence and disorder (Hailey, 2025). A recent survey experiment further shows that, all else equal, NYC families prefer schools that current students believe are safe (Hailey, 2022b).

Student curricular satisfaction also closely links to psychosocial measures of adolescents' subjective assessment of their school quality. Huebner (1994) defines school satisfaction as "student's evaluation of the positiveness of his or her school experiences *as a whole*." School satisfaction measures commonly assess students' evaluations of school-related curricula and extracurricular activities. Students who report greater school satisfaction tend to exhibit better socio-emotional well-being and lower absenteeism, but the relationship with academic achievement remains unclear (Huebner & Gilman, 2006; Suldo et al., 2022).

While there is limited research on the benefits of schools' student satisfaction, research suggests that families may be willing to trade-off academic quality in exchange for student satisfaction (Debs et al., 2023; Warikoo, 2024). Specifically, Jacob and Lefgren (2007) find that parents tend to prefer teachers who promote student satisfaction over those who improve student achievement. Similarly, Ainsworth et al. (2023) shows that families prefer schools

with a curricular focus that their student will enjoy, even at the expense of school value-added, regardless of whether value-added information is available.

1.2 Measuring student safety and student satisfaction in NYC

Since 2006, NYCDOE has conducted annual surveys with teachers, parents, and sixth through twelfth grade students at every public school. NYCDOE originally designed the survey to provide insights into school engagement, communication, and safety (Nathanson et al., 2013). The surveys represent students' perceptions of their schools, as NYCDOE aims to survey the full population of *all* students enrolled in each school. Each spring, approximately 80% of all high school students complete the survey (NYC DOE, 2023).

While NYCDOE students answer multiple survey questions related to their perceptions of school safety and satisfaction, in this study we focus on two specific student survey questions that make the basis for our natural experiment. For the school safety measure, students report how much they agree with the statement: "I am safe in the hallways, bathrooms, and locker rooms at my school." On the other hand, for the student satisfaction measure, students are asked how much they agree with the statement: "My school offers a wide enough variety of classes and activities to keep me interested in school."[6]

1.3 The release of school information

In 2007, the NYCDOE printed its first high school directory. These physical 600-plus page telephone book style directories included a profile page for each NYC high school. The profiles described each school's location and program highlights (i.e. general description, courses, and admission requirements and eligibility). Since 2011, the directories have presented some version of high schools' graduation rates. According to NYC school guidance counselors and a recent survey of NYC eighth grade parents, families use the directory as their primary information source on potential schools (Idoux & Corradini, 2024; Sattin-Bajaj et al., 2018).

In this study, we leverage a shift in the school performance information that NYCDOE published in the high school directory in 2016, as well as a shift in how the directories were published starting in 2017. First, in 2016, the DOE released information about school safety and student satisfaction on the high school directory profiles for the very first time.[7] Drawing on schools' student surveys from two years prior, the directory profiles listed the percent of

[6]This phrasing is similar to that used by Ainsworth et al. (2023) to measure students' satisfaction, where parents rate how much they agree that: *My child will enjoy this track's curricular focus.*

[7]See Figures A1 and A2 for examples of school profiles published in the Directory in 2016 and 2017.

students who "feel safe in the hallways, bathrooms, locker room, and cafeteria" and the percent of students who "feel that this school offers a wide enough variety of programs, classes, and activities to keep them interested in school." The new items were included alongside schools' graduation and college enrollment rates, which had already been componted of the directory since 2011 and 2012, respectively.

Next, in 2017, the DOE moved the high school directories to an online format through the new SchoolFinder website to ease the school admissions process (Disare, 2016).[8] SchoolFinder offered three key features over the printed directories. First, families could access the school directory information on their phones and computers. Second, NYCDOE published the online directories in English and Spanish, while families would have to request Spanish versions of the printed directory. Third, families could use SchooolFinder's digital search feature to find schools with particular course and extracurricular offerings (i.e. soccer, art, etc.). Publishing the directories online potentially impacted the visibility of all the school characteristics. As such, we consider the online publication of the high school directory as an additional information shock for all academic and non-academic school performance data.[9]

2 Data

We use three types of data to investigate the impacts of non-academic school information on students' ranked school choices. First, we use a database with every NYC families' ranked-ordered list of preferred high schools from 2012 to 2019. Second, we use NYCDOE administrative data that contain schools' performance and demographic characteristics. Third, we use data on the academic and non-academic school performance information published in the NYCDOE directory. Below we describe these data sources in detail.

2.1 Families' Preference Ranking Lists

NYC students are not automatically assigned to attend a neighborhood high school. Since 2004, NYCDOE requires all students enrolling in NYC public high schools to submit applications. On these applications, families list their rank-ordered preferences of up to 12 programs out of 700 possible programs in 400 schools. NYCDOE uses a deferred acceptance, which is a strategy-proof algorithm that matches students to schools based on students' ranked

[8] An archived example can be found here: https://web.archive.org/web/20161129140243/http://schoolfinder.nyc.gov/#/schools/02M416/keywords:eleanor

[9] The school performance data began including school attendance rates alongside school graduation and college enrollment rates and the school safety and student satisfaction measures. As we show in Section 3, attendance rates describe a very similar dimension of schools as graduation and college enrollment rates. Therefore, we combine these three school characteristics into a single school academic index in Section 2.

preferences and schools' admission requirements and priorities (Abdulkadiroğlu et al., 2020). Students' rank-ordered lists are consequential for their high school assignments. NYCDOE matches 44% of students to attend the first-ranked school on their application, and 80% to one of their top-three ranked schools. On average, about 77,000 students submit high school applications each year, across our study period (2011-12 to 2018-19). Students submit seven schools on their preference lists, on average.

We obtain data on families' ranked high school preferences from NYCDOE administrative data distributed through the Research Alliance for NYC Schools.[10] Our dataset contains separate observations for each student-by-ranked-school combination. We follow Ainsworth et al. (2023) and calculate a measure of within-family preference percentile ranking (PPR) by dividing a school's rank in the family's preference list by the number of schools listed. The PPR is ordered such that a value of 1 indicates a family's most preferred school.[11]

These data also include students' race/ethnicity, gender, residential borough, home language, and eighth grade standardized test scores. It also contains indicators for whether the student received free lunch and their special-education and English language learner status. Additionally, we calculate student's neighborhood income by merging students' residential zip code with annual adjusted gross income data from the IRS Statistics of Income Tax Stats. Lastly, we proxy for distance between a student's home and each school ranked in their application by calculating the aerial distance between the centroid of their residential Census tract and the corresponding school geographic coordinates.

2.2 School Characteristics

We also obtain school-level performance and demographic data from the NYCDOE. These data include student safety and student satisfaction data from the NYCDOE School Survey Archive, as well as graduation, college enrollment, and attendance rates from the NYC School Quality and Progress Reports. We also have information about school demographics, including poverty rates (as proxied by free-lunch eligibility), incoming students' 8th grade proficiency rates, and the enrollment shares of students with disabilities, English Language Learners, and racial/ethnic groups from the NYCDOE Demographic Snapshots.

These data include the most recent school characteristics from the academic year that students applied to school. They were not yet published in the directories nor in the NYC School Quality Reports when students submitted their applications. For example, when

[10] The high school application data are compiled by Sean Corcoran.

[11] Due to computational limitations, we focus our analysis on student's lists of ranked schools and exclude schools outside their ranked lists from their choice set. Our analysis tells us about students' within-list ranking, rather than about students' preferences across every possible school. Otherwise, we would have to consider the Cartesian product of 70,000 applicants and 400 schools in each of the eight years of data.

assessing school preferences in 2019, we account for the school graduation rates in 2019; these data would not be accessible to families in the NYC Quality Report until 2020.

We also obtain measures of peer quality and school value-added from various NYC's DOE websites.[12] We specifically obtain schools' average SAT scores going back to 2012. NYCDOE calculates a measure of school value-added by generating an achievement index for each school (based on various academic metrics, including graduation, regents, and SAT scores), while controlling for student characteristics, such as incoming test scores, IEP status, and economic need. We use the earliest available measures of value-added from 2015.

2.3 High School Directory Information

We obtain information on schools' academic and non-academic performance as it is printed in the high school directory. Notably, the directory includes data on student safety, student satisfaction, graduation rates, college enrollment rates, and attendance rates, which are sourced from the NYCDOE School Survey and the NYC School Quality and Progress Reports. The high school directory data are lagged by two years due to the timing of their availability. The NYCDOE prints the directory before the most recent School Survey and Quality Reports are published.

The school characteristic data are distinct from those in the school directory in three ways. First, NYCDOE directly advertises the directory information to families applying to high schools, making it the most salient and accessible source of school information for applicants. Second, the directory only includes lagged data from two years prior to its release. Third, school demographic data are not available in either source. However, families can access demographic information through alternative sources, such as visiting schools in person or consulting non-profit school review websites (e.g., InsideSchools.org or GreatSchools), or NYC and the State Department of Education school report cards.

2.4 Standardized measures of school characteristics/information

Because the school directories provide several pieces of information, we combine similar characteristics into an index. We compute an "academic" index by taking a factor analysis (using the principal-component factor method) of the directories' graduation, college enrollment, and attendance rates (in years when available), and then predict the first unrotated factor. We create two versions of the index, one version based on the yearly information published in the school directory, and the other version based on the average directory information between 2016 and 2017. Appendix Table A1 shows the weights used to compute each index.

[12] See for example: https://tools.nycenet.edu/guide/2016/#dbn=02M411&report_type=HS.

Lastly, we follow the literature and convert all of our measures of school characteristics into percentile ranks (Ainsworth et al., 2023; Campos, 2024). To do this, we rank schools in terms of the corresponding characteristic and then divide the school's within-year rank by the total number of schools with non-missing data. We order this measure such that a value of one indicates the top ranked school in the district for the corresponding characteristic.

2.5 Descriptive Statistics

Table 1 presents averages and standard deviations for our analytic sample of NYCDOE public high schools and student applicants, during our study period. The analytic sample includes 437,764 students who applied to NYC public high schools, listing 339 schools on their applications.

On average, the schools listed on students' applications had a preference percentile rank of 0.59. The PPR average leans to the right of the 50th percentile because PPRs range from 0.083 to 1, which excludes the value of zero.[13] Among these schools, 82% of students felt safe in the school and about three-quarters were satisfied with the school's program, class, and activity offerings. The average graduation rate for schools in our sample was 74%, the college enrollment rate was 55%, and the attendance rate was about 87%.

Among applicants, three-quarters qualified for free or reduced-price lunch and their average neighborhood income was about $53,000. The racial composition of applicants was 43% Latino, 29% Black, 15% Asian, and 13% White.

3 Multidimensionality of school quality

Since NCLB, public and academic discourse has emphasized academic-based school characteristics. In response to this limitation, ESSA requires that schools collect and publish information about non-academic-based school characteristics. However, if schools are unidimensional, then achievement-based school qualities may encapsulate other dimensions of schools. To assess this, we explore whether non-academic based school characteristics provide information beyond the academic achievement of schools.

Using data from 2011-12 through 2014-15 (before the information shocks), we find that schools' student safety and satisfaction provide information about dimensions of schools beyond their academic quality. This is in line with previous work on non-academic school quality (Beuermann et al., 2023; Crespin, 2025; Hailey, 2025).

[13]This is due to our decision to only focus on students' ranked list of schools, without adding outside options that would have PPRs of zero.

First, simple factor analysis shows that two factors are required to explain more than 80% of the total variance in the high school directory information that we focus on in this study. Figure 1 shows that the first unrotated factor is most strongly associated with graduation, college, and attendance rates, and least associated with student satisfaction. The second unrotated factor has the opposite relationship. Schools' student safety is moderately associated with each of the two unrotated factors.

Second, we find that a traditional measure of school performance–average SAT scores–is less correlated with schools' non-academic characteristics, compared to the correlation with the academic index. Table 2 shows the correlation matrix for these school characteristics. More specifically, average SAT scores are weakly to moderately correlated with student safety and student satisfaction–the correlation coefficients are 0.34 and 0.12, respectively.[14] On the other hand, our academic index has a strong correlation with average SAT scores of 0.74. These correlations suggest that schools are multidimensional, and non-academic characteristics invoke an aspect of schools beyond traditional measures of schools that are based on academic features, such as test scores and graduation rates. The last row of the table shows that school value-added most strongly correlates with student safety and the academic index (correlation coefficients of 0.36 and 0.33) and most weakly associates with student satisfaction and average SAT (correlation coefficients of 0.14 and 0.00).

To further quantify the multidimensionality of schools, we use already publicly available school characteristics to predict the high school directory information that would be available in each year during the pre-shock period, as well as schools' average SATs and school impacts/value-added. Table 3 presents the estimated R^2 from simple linear regression models.[15] Columns (1) and (2) show that more than 75% of the variation in average SAT scores and the academic index can be explained by already publicly accessible school characteristics. However, less than half of the variation in student safety or student satisfaction can be explained by very similar models, as shown in columns (3) and (4). These results are in line with Crespin (2025), who finds that in Chicago, traditional school data explain far more of the variation in test proficiency rates than in school climate. Similarly, column (5) shows that only 22% of the variation in school impacts can be explained by these models.[16]

[14]The correlation between student reported safety and student reported curricular satisfaction is moderate, with a correlation coefficient of 0.47.

[15]These models control for the average SAT score (except in column 1), the academic index (except in column 2), and the NYC calculated school value-added (except in column 5). These models also control for high schools' incoming 8th grade proficiency, poverty rates, racial composition, as well as the shares of English Language Learners and of students with disabilities.

[16]The low predictability of school value-added is similar to findings by Crespin (2025) and Imberman and Lovenheim (2016).

4 Baseline Preferences

Table 4 shows how families' preference rankings were bivariately associated with schools' student safety, student satisfaction with course and extracurricular variety, and school academics before the information shocks.[17] Each of the three characteristics is significantly and positively associated with families' PPRs during the pre-shock period. For ease of exposition, all estimates are multiplied by 10, so a 10-percentile higher school academic index was associated with 1.3 percentiles higher family preference ranks. Consistent with previous research (Hailey, 2025; Harris & Larsen, 2023), the associations for student safety and student satisfaction were smaller, ranging from two-fifths to two-thirds the magnitude of the academic index's association. A 10-percentile higher student safety or student satisfaction is associated with a 0.5 and 0.8 percentile higher family school preference ranking, respectively.

Figure 2 presents heterogeneity in the pre-shock association between families' PPRs and school characteristic percentile across various subgroups: student performance (below/above median incoming math test score), family income (eligible/ineligible for subsidized lunch), family neighborhood income (below/above median), and by student race.[18]

Panel (a) of Figure 2 first shows that students with lower-incoming math scores have a weaker association between families' PPRs and schools' student safety, compared to higher-achieving students (pink estimates). This pattern aligns with the literature, which finds evidence that parents of high-achieving students have a stronger aversion to crime victimization and school violence/disorder (Beuermann et al., 2023; Hailey, 2025). Our estimated association for higher-performing students is four times that of the lower-achieving students.

Lower-income students, as proxied by FRPL-eligibility, also have a weaker association than higher-income students (red estimates). This pattern is in line with the literature showing that higher-income families' are more likely to avoid schools with higher levels of violence and disorder, and students perceptions of disorder (Hailey, 2025). However, students from lower-income neighborhoods have a stronger association between schools' student safety and families' PPRs compared to students from higher-income neighborhoods (blue estimates). The gaps by income are substantially smaller than that by incoming math achievement.

Panel (b) shows that students with higher-incoming math scores have a 65% larger association between families' PPRs and student satisfaction than lower-achieving students, and is in line with Ainsworth et al. (2023). The pattern continues between higher- and lower-income families. Panel (c) shows that higher-achieving and higher-income students also have a stronger preference for schools with higher academic indices, which is in line with related

[17] The three school characteristics are based on the average measures between 2016 and 2017 for each school characteristic, which are the main information shocks we focus on in this paper.

[18] Appendix Table A2 summarizes this information numerically.

work (Abdulkadiroğlu et al., 2020; Hailey, 2025).

In terms of race/ethnicity, panels (d) through (e) in Figure 2 show that before the initial information shock, Asian students exhibited the strongest association between PPRs and schools' student safety percentile, followed by Latino, White, and Black students.[19] Moreover, Asian and White students' PPRs had stronger associations with schools' student satisfaction than Black and Latino students. Similarly, Asian students had the strongest associations between families' PPR and schools' academic index, followed by White students and then Black and Latino students, which is in line with the literature (Abdulkadiroğlu et al., 2020; Corcoran et al., 2018). Importantly, the heterogeneity in school choices by student academic achievement, income, and racial background could be due to several factors, including differences in students' preferences and access to information, or schools' admission criteria (Corcoran et al., 2018; Hastings & Weinstein, 2008).

This descriptive approach to preference estimation likely suffers from omitted variable bias. Reassuringly, we find similar patterns to those found in the literature. In the following section, we conduct careful analysis to differentiate between associative and causal changes in response to non-academic information shocks. Furthermore, we explore whether the heterogeneity in the associations between subgroups shifts after the information shocks.

5 Identification Strategy

It is difficult to identify families' isolated preference for one school characteristic over another, because school factors often correlate in unobservable ways. In this section, we describe how we use the NYC school directory information shocks to estimate the impact of non-academic school quality information on families' school selections. Figure 3 plots raw trends of the associations between families' preference percentile rankings (PPR) and school characteristics from the high school directory between 2012 and 2019.[20] The vertical dashed black line marks the start of the non-academic information shock in the high school directory, while the vertical dashed gray line symbolizes the beginning of the online high school directory.

The figure shows the associations are generally stable before 2016. The largest association (0.13) is between families' PPRs and the academic index, which estimates an increase of 1.3 prefence percentile ranks for a 10-percentile increase in the academic index. Consistent with

[19] Hailey (2025) finds that Asian and White families have the strongest correlation between families' rank order of schools and school violence/disorder and student perception of security in NYC in 2013, however, we find that Latino students have the second-strongest correlation after Asian students between 2012 and 2015. Note that our student safety measure differs from Hailey (2025).

[20] We estimate the association between PPR and each of the three school characteristics by conducting separate bivariate regressions for each cohort. We use the percentile of the average between 2016 and 2017 for each school characteristic, which are the initial information shocks we focus on in our main approach.

previous research (Hailey, 2025; Harris & Larsen, 2023), the associations for student safety and student satisfaction were smaller—ranging from one-third to two-thirds the magnitude of the academic index's association (0.05 and 0.08, respectively). The figure shows that the estimated associations for all school characteristics begin to increase in 2016 or 2017, at the same time that the student safety and satisfaction information are first included in the high school directory and when the directory begins to be published online. These changes suggest that the information shocks may have led to changes in families' preferences for academic and non-academic school characteristics. However, this descriptive approach likely suffers from omitted variable bias. In the rest of this study, we conduct careful analysis to differentiate between associative and causal changes in response to non-academic information shocks.

We follow a process like that of Ainsworth et al. (2023) to explore how providing families with novel non-academic school quality information impacts their school choices. More specifically, we examine how families' preference percentile rankings (PPR) change between the pre- and post-information shock periods as a function of school quality. To do this, we conduct regressions of the following form:

$$\begin{aligned} ppr_{icst} = \beta_0 + \left(\beta_1 \cdot pr^{safety}_{s,2016-2017} + \beta_2 \cdot pr^{satisfaction}_{s,2016-2017} + \beta_3 \cdot pr^{academic}_{s,2016-2017}\right) \cdot Post_{t\geq 2016} \\ + \gamma D_{ist} + \delta_{itc} + \mu_{isc} + \Gamma \mathbf{X_{st}} + \varepsilon_{icst} \end{aligned} \tag{1}$$

where ppr_{icst} is the preference percentile ranking (PPR) by family i, who belong to demographic cell, c, for school s based on their submitted school applications in year t.[21] We define demographic cells by the combination of student race, gender, subsidized lunch eligibility, eighth grade test score tercile, residential borough, ELL status, home language, special-education status, and residential zip code's average income tercile.

Our key explanatory variables of interest are $pr^{safety}_{s,2016-2017}$ and $pr^{satisfaction}_{s,2016-2017}$, which are school s's percentile based on the 2016 and 2017 average student safety or student satisfaction, respectively. We base these percentiles on averages from the 2016 and 2017 data because directory information was updated annually, making these the initial non-academic information that were available in both the physical and online directories. Furthermore, the 2016 and 2017 information information is lagged by two years, meaning that these information shocks were not endogenously affected by school changes in response to either information release. We interact these terms with a *Post* indicator, which switches on starting in 2016.

[21] Due to computational limitations, we focus our analysis on student's lists of ranked schools and exclude schools outside their ranked lists from their choice set. This means that our analysis tells us about students' within-list ranking, rather than about students' preferences across every possible school. Otherwise, we would have to consider the Cartesian product of 55,000 applicants and 400 schools in each of the eight years of data.

As discussed in Section 1.3, each year's high school directory included information about graduation, college enrollment, and attendance rates, which may have made these academic school characteristics more salient to families. Thus, in our main model, we allow for the effect of the academic index, $pr^{academic}_{s,2016-2017}$, to vary post-2016. We also include a vector, $\mathbf{X_{st}}$, which controls for schools' most recent measure of student safety, student satisfaction, and academic index. Therefore, our shock measures capture reactions to information that is beyond reactions to the latest academic and non-academic conditions in schools.[22]

The school choice literature emphasizes families' strong preference for home-to-school proximity (Abdulkadiroğlu et al., 2020; Hastings & Weinstein, 2008). Therefore, our model controls for the natural log of distance, D_{ist}, between student i's neighborhood to school s in the year of their application t.

To identify changes in preferences for school characteristics over time, we examine changes in preferences by students from the same demographic cells.[23] Specifically, we include year-by-demographic-cell fixed effects, δ_{itc}, to control for any systematic time-varying shifts in preferences due to external factors across demographic cells and years, for example changes due to school openings and closures. We also include school-by-demographic-cell fixed effects, μ_{isc}, which control for unobserved preferences for schools that are fixed over time within demographic cells, such as school reputation or feeder patterns. The inclusion of these two fixed effects means that our parameters are identified off of changes in the difference in preferences across schools within demographic cells before and after the information shocks take place. The β_q coefficients represent DID estimates of the impact of school characteristic q having a higher percentile rank on families' PPRs after the information release relative to before the release.[24] Standard errors are clustered at the school-year level.

Two main assumptions underlie our main DID approach. The first is that families' preferences were not trending differentially for each school characteristic prior to the information shocks. We test for differential trends by conducting event study analyses that explore the impact of the school information on families' PPRs on a yearly basis before and after the

[22] In Section 6.1.3, we show that our estimates are robust to excluding the contemporaneous measures of safety, satisfaction, and academics.

[23] In our context, we are not able to compare within-student differences in preferences for school characteristics over time because almost all students apply for high schools in only one year, and, therefore, the same student's preferences cannot be compared before and after the information shocks.

[24] Note that the model excludes school characteristics without the post indicator because, like other time-invariant school characteristics, these would be absorbed by the school-by-demographic-cell fixed effects.

shocks take place. More specifically, we conduct regressions of the following form:

$$ppr_{icst} = \beta_0 + \sum_{\substack{\tau=2012,\\ \tau\neq 2015}}^{2019} \left(\sum_{q=1}^{3} \left(\beta_{q,t} \cdot pr_{st}^{q} \cdot 1(t=\tau) \right) \right) + \gamma D_{ist} + \delta_{itc} + \mu_{isc} + \Gamma \mathbf{X_{st}} + \varepsilon_{icst} \quad (2)$$

where variables are the same as in equation 1, except that the $\beta_{q,t}$ coefficients represent the impact of characteristic q's percentile on families' PPRs in relative period t, compared to the impact in 2015 before the information shock takes place.[25]

The second main identification assumption required by the DID framework is that the school characteristics of interest, conditional on other school factors, are not correlated with secular changes in the unobserved characteristics of families and schools that could independently affect families' PPRs. This assumption is not directly testable, however, the district did not begin to use these school factors for accountability during our sample period, and the non-academic characteristics were only used for informational purposes. This suggests that there would not be other intentional concurrent changes attached to the release of the information that may affect families' preferences in other ways.

Equation 1 includes one general information shock for each of the school characteristics that capture both the physical and online directory information shocks. In order to parameterize the dynamic reactions to the physical and online directory information shocks, we modify the estimating equation to account for the subsequent releases of the information. The model we estimate is:

$$\begin{aligned} ppr_{ist} = \beta_0 &+ \left(\gamma_1 \cdot pr_{s,2016}^{safety} + \gamma_2 \cdot pr_{s,2016}^{satisfaction} + \gamma_3 pr_{s,2016}^{academic} \right) \cdot 1(t \geq 2016) \\ &+ \left(\lambda_1 \cdot pr_{s,2017-2019}^{safety} + \lambda_2 \cdot pr_{s,2017-2019}^{satisfaction} + \lambda_3 pr_{s,2017-2019}^{academic} \right) \cdot 1(t \geq 2017) \quad (3) \\ &+ \gamma D_{ist} + \delta_{ict} + \mu_{ics} + \Gamma \mathbf{X_{st}} + \varepsilon_{icst} \end{aligned}$$

where $pr_{s,2016}^{safety}$, $pr_{s,2016}^{satisfaction}$, and $pr_{s,2016}^{academic}$ are the 2016 version of the information shocks. The variables $pr_{s,2017-2019}^{safety}$, $pr_{s,2017-2019}^{satisfaction}$, and $pr_{s,2017-2019}^{academic}$ are based on the average online information between 2017 through 2019 for each of the three school characteristics. All other variables are defined as above.

[25] As in equation 1, we use the 2016 to 2017 average for each of the three school characteristics.

6 Results

We begin our empirical analysis of the overall non-academic information impacts by examining event studies and DID results. We then proceed to explore information impact heterogeneity and provide robustness checks.

6.1 Overall Information Impacts

Figure 4 shows event study estimates of the impact of non-academic and academic school information on families' PPRs before and after the information shocks take place, all of which are estimated in the same regression through equation 2. The three event studies show relatively flat relationships that revolve around the zero line between families' PPRs and the percentile of schools' characteristics before the 2016 information shock. The lack of differential pre-trends provide supporting evidence for the parallel trends assumption.

The green (circles) event study shows that the 2016 release of non-academic school information led to an immediately clear and significant upward level shift in families' preference rankings for schools with better student safety. However, the purple (triangles) event study suggests only a slight and not statistically significant reaction to information about student satisfaction in the immediate term. Importantly, the initial information release of safety and satisfaction information did not immediately impact families' preference rankings for schools' with a better academic index (gray squares event study). This lack of immediate reaction reinforces the fact that there was no change in the provision of school academic quality information in 2016.

Between 2017 and 2018, there is a sharp reaction to information about student satisfaction and an increasingly positive reaction to the academic index. This takes place as the NYCDOE released and promoted the online High School Directory, potentially increasing the salience of the non-academic and academic information.[26] However, there is only minimal additional reaction to the student safety information, beyond the initial 2016 impact.

Table 5 summarizes the DID results based on equation 1. All information shock estimates are multiplied by 10, so they show the effect of a 10-percentile increase in the school information on families' PPRs post-release. Column (1) shows that relative to the pre-shock period, families' preference rankings for schools increased by 0.13 and 0.12 percentile points for every 10-percentile higher student safety and for every 10-percentile higher student satisfaction, respectively. Both estimates are statistically significant at the 1% level. Academic information had a negligible and statistically insignificant impact on families' PPRs.

[26] In Section 7.2, we discuss potential information mechanisms that help explain these dynamics.

Given the different baseline associations across school characteristics discussed in Section 4, our estimates suggest that providing families with student safety information increases the association between PPRs and school safety by 25%. For student satisfaction information, the increase is 15%. To put this into context, Ainsworth et al. (2023) find that a school value-added information shock in Romania produced an 11% increase in the association between families' PPRs and school value-added percentile.[27] This comparison highlights that safety information has more than twice the impact of school value-added, while satisfaction information produces a similarly sized effect.

Column (2) only differs in its inclusion of log distance, which shows that controlling for distance does not impact our main estimates, which suggests that our specification is not confounded by preferences related to proximity. Furthermore, the negative coefficient on distance shows that farther proximity leads families to rank schools lower, which is in line with the literature (Abdulkadiroğlu et al., 2020; Hastings & Weinstein, 2008).

6.1.1 Heterogeneity of Information Impacts across Subgroups

Due to pre-shock heterogeneity in preference rankings for different school characteristics, as described in Section 4, it is possible that the information shocks had heterogeneous effects by student subgroups. In Table 6 we examine information impact heterogeneity by student academic achievement (based on incoming math scores), socioeconomic background (based on eligibility for subsidized lunch or neighborhood income), and by student race.[28]

Columns (1) and (2) in the first row of Table 6 shows suggestive evidence that lower- and higher-achieving students reacted similarly to the safety information in absolute terms, with families' preferences for schools with a 10-percentile better student safety measure being 0.14 percentile ranks higher relative to the pre-shock period (p-value$\leq$ 0.01). Appendix Figure A7 displays the information impacts by math performance decile.

Columns (3) and (4) of Table 6 show that lower-income students react more strongly to the safety information compared to higher-income students, as measured by subsidized lunch eligibility. A similar pattern of information impacts emerges by neighborhood income. Columns (5) and (6) in Table 6 shows these results for students from below/above median income neighborhoods. Students from the lowest-income neighborhoods have a positive and statistically significant reaction to the safety information (p-value$<$0.01), while those from

[27] Focusing on a top-ranked schools approach, Campos (2024) finds that providing families with school value-added information in Los Angeles leads to about an 8% increase in the value-added of families' top-ranked school choice. On the other hand, Hastings and Weinstein (2008) find that providing families with information about school test score levels in Charlotte-Mecklenburg led to an 89% increase in the test score levels of families' top-ranked school choice.

[28] Appendix Figures A3, A4, A5, and A6 present event studies for each subroup.

higher-income neighborhoods do not have a significant reaction to the safety information. Appendix Figure A8 demonstrates this same pattern by neighborhood income decile.

Due to the heterogeneity in baseline preferences described in Table 4, the initial safety information shock causes a substantially larger percentage change impact for lower-achieving students (65%) than for higher achieving students (17%). This also leads to a stronger impact for students with subsidized lunch (around 31%) than for ineligible students (15%).

The second and third rows in Table 6 show that all students across achievement and income have similarly positive reactions to student satisfaction information.[29] On the other hand, only higher-income students have statistically significant reactions to the academic information. The patterns are similar in terms of percentage change.

In terms of heterogeneity by student race, Asian and Latino students react most positively to student safety information.[30] White students have a slightly negative reaction to student safety information, although not statistically significant, which is a similar response by students from higher-income neighborhoods.[31] Lastly, in absolute and percent change terms, White students have the strongest reactions to academic information compared to non-White students, although the standard errors for this estimate are large.[32]

6.1.2 Discussion of Information Shock Results

One of our key findings is that families value non-academic school information beyond academic information. Four recent papers that have studied the valuation of non-academic school characteristics are Ainsworth et al. (2023), Beuermann et al. (2023), Hailey (2025), and Harris and Larsen (2023). Those studies use selection on observables models with school applications data to examine families' preferences for student satisfaction with curricular focus, non-academic outcomes (crime, teen motherhood, and labor market participation), and school safety/extracurriculars.[33] Our results contribute to this growing literature, by demonstrating that families react directly to non-academic school quality beyond academics when they receive a plausibly exogenous shock of information in a clear and accessible manner.

Several clear patterns emerge from our analysis. Families consistently valued school safety

[29] However, Appendix Figures A7, A9, A8, and A10 suggest slightly stronger reactions by higher-achieving and higher-income students, in absolute terms.

[30] In percentage terms, Black and Latino students react most strongly to safety information, relative to the baseline associations.

[31] Hailey (2025) similarly finds that White NYC students rated schools that teachers perceived as safe lower on their applications, a pattern driven mainly by schools with larger White student populations.

[32] Our estimates show that, on average, White students are the least willing to travel when ranking schools, while Black students are the most willing to do so.

[33] Crespin (2025) shows that homebuyers value school climate information in the housing market, but this approach is limited to families looking for and able to afford to purchase a home, which our paper is able to address by using applications data for all students in the district.

information, particularly among lower-income, Asian, and Latino students.[34] The academic information effects were particularly large for higher-income students' school preferences. Our subgroup analysis for academic information is consistent with studies, showing that advantaged families were more responsive to interventions that increased exposure to academic information (Cohodes et al., 2022; Corcoran et al., 2018; Hastings et al., 2007).

Notably, the information shocks did not diminish most subgroup differences in student preferences for school academic and nonacademic characteristics. In fact, many of the preference disparities across student racial background for school safety and academic information increased after the information shocks. This was due to Asian students' school selections having closer alignment with school safety and academic characteristics before the information shock and the information shocks having larger or similar effects relative to their peers.

This heterogeneity provides researchers and policymakers with valuable insights into different families' tradeoffs when considering potential schools. It suggests that, while school districts and scholars have traditionally emphasized providing academic performance and value-added data to inform families' school selections, non-academic characteristics—such as student safety and satisfaction—may be particularly salient to some families' school choices.

6.1.3 Robustness

We now test the sensitivity of our main findings by conducting a series of robustness checks. Appendix Table A3 shows the results for various specifications where we vary the controls included in the model. Column (1) presents our main results for comparison. The estimates are very similar if we exclude time-varying contemporaneous safety, satisfaction, and academic school characteristics in addition to excluding the natural log of distance in column (2), or if we remove only one of these two sets of controls in columns (3) and (4). The non-academic estimates are similar and remain statistically significant at the same level of confidence if we control for time-varying school demographics in column (5). However, controlling for school demographics decreases the academic estimate towards zero, which is due to the strong correlation between demographics and academic measures. In column (6), we show that our estimates only change slightly when we control for pre-trends for safety, satisfaction, and the academic index. The pre-trend coefficients are near zero and not statistically significant.[35]

In Appendix Table A4, we allow for directory information to vary from year to year. The results emphasize that the information effects are consistent, but smaller than the initial

[34] In concurrent work, Rachkovski (2025) also finds that in Israel, lower-income families' school choices are more responsive to increased availability of school violence information than higher-income students.

[35] Full estimates available upon request.

non-academic information shocks. This suggests that the student safety information had a sticky impact, while most of the satisfaction effect came from year-to-year variation.

Appendix Table A5 displays the results when we vary how we define families' preferences, by focusing on whether students' rank a school in their top three choices.[36] For this analysis, the outcome is an indicator for whether or not the specific chosen school was ranked as the corresponding choice. Therefore, the outcome is zero if the school was ranked by the student, but not in the corresponding set of top choices. Understanding how information impacts the top-ranked schools is particularly important for students' ultimate high school enrollment, since 44% of eighth graders were assigned to their first-choice school, 66% to their top two ranked schools, and 80% to the their top three ranked schools. Column (1) shows that families are 0.23 and 0.16 percentile points more likely to rank a school in their top 3 choices in response to a 10-percentile higher student safety or satisfaction, respectively, relative to before the information shock. The estimated impact for the academic index is the smallest coefficient, but is still statistically significant at the 5% level. However, this approach does not account for how many schools families rank in their application.

Columns (2) and (3) show that the student safety and satisfaction information shocks still impact families' preferences in their decisions on which schools to rank as their top and second-preferred school, but this marginal impact weakens as we focus on the most preferred schools. Safety and satisfaction information has diminishing, although still significant, impacts as the decision becomes more high-stakes for students' actual enrollment match.[37] On the other hand, the academic information impact is entirely concentrated in lower-stakes ranking margins, and has no significant impact for the highest stake schools choices. This pattern is consistent with research that finds that academic information has stronger impacts on students' lower-ranked school selections (Ainsworth et al., 2023; Valant & Weixler, 2022).

7 Information Dynamics and Mechanisms

7.1 Does the format of information provision matter?

As suggested by the event study in Figure 4, there was an immediate reaction to the student safety information, but the significant reaction to student satisfaction information was delayed. Columns (3) and (4) in Table 5 summarize the dynamic DID results based on equation 3. The first three rows of estimates present impacts from introducing the 2016 student

[36] 88% of students submit at least three choices in their high school applications.

[37] In terms of percentage change, student safety information causes a 25% to 74% increase in the likelihood of schools with a 10-percentile safer school to be ranked in the top three choices. Student satisfaction information has a consistent impact across these top three choices, ranging from 9% to 10% impact.

safety and satisfaction information into the physical high school directory for the very first time, as well as allowing for additional impacts from the academic information. The fourth through sixth rows present the impacts from the NYCDOE's interactive online high school directory–School Finder.[38]

The first row in columns (3) and (4) shows that relative to before the information shock, families' preference rankings for schools increased by about 0.1 percentile points for every 10-percentile improvement in a school's student safety (statistically significant at the 1% level). This estimate corresponds to an increase of 21%, relative to the association between families' PPRs and student safety during the pre-shock period.

This reaction suggests that when safety and satisfaction information is added to the physical high school directories, families understand and incorporate schools' student safety information into their school selections. However, the second row's estimates show that families' do not significantly react to new information about schools' student curricular satisfaction, even though in the pre-shock period student satisfaction was more strongly associated with PPRs than was schools' student safety. The third row again shows a null differential reaction to academic information in 2016.

Next, we find that the online directory did not significantly impact families' preferences for student safety beyond the initial impact from the physical information release.[39] On the other hand, the fourth and fifth row estimates demonstrate that the online directory led families to increasingly prioritize schools with better student satisfaction and academic index. Specifically, there was a 13% and 10% increase in the relationship between families' PPRs and schools' student satisfaction and academic index, relative to the pre-shock period, respectively. Both estimates are statistically significant at the 5% level. These estimates emphasize that all of the student satisfaction impact is driven by the online High School Directory information shock. These student safety and satisfaction information impacts suggest that their inclusion in the directories offered families access to valuable information that may not have been readily available or easily accessible through other channels in the pre-information shock period (i.e. school visits, online school quality, social networks).

7.2 Potential Mechanisms

In this subsection we investigate potential mechanisms behind the immediate reactions to student safety information, but delayed responses to information about schools' student

[38]The online information shocks are based on the averages information from 2017 through 2019 for each school characteristic.

[39]This means that the impacts from the original safety information shock were sustained through the online release of the information, but the online release did not cause families to behave significantly different than when the information was published in the physical directories.

satisfaction and academics. We consider two main channels: (1) information salience and search costs, and (2) information architecture and formatting.

7.2.1 Information salience and search costs mechanism

Prior to the information shocks, families preferred schools with higher levels of student safety, satisfaction, and academic outcomes. However, accessing reliable information on these dimensions required substantial cognitive and time investments. Families often had to engage in resource-intensive activities, such as visiting schools, navigating complex district or nonprofit websites, or relying on informal social networks (Beuermann et al., 2023; Sattin-Bajaj & Roda, 2018; Sattin-Bajaj et al., 2018).

Research shows that when valuable information becomes more salient, individuals face lower search costs and can better incorporate this information into their economic decisions (Bordalo et al., 2022). In the context of school choice, the NYCDOE's efforts to enhance the visibility of academic and nonacademic school information likely reduced the cognitive and time burdens families faced when searching for school quality data. As a result, families would become better equipped to identify schools that aligned with their preferences, increasing demand for those schools (Campos, 2024).

One key mechanism driving families' immediate response to the publication of school safety information was likely the increased accessibility of these data. By reducing search costs, families could more easily consider safety in their school decisions. Consistent with this, we find the largest responses among lower-income and Latino families—groups that prior studies suggest highly value school safety but face the greatest barriers to accessing such information (Hailey, 2025; Rhodes & DeLuca, 2014; Sattin-Bajaj, 2014). Notably, we do not find additional significant responses when the directory moved online, possibly because the online format did not further elevate the prominence of safety information.

Additionally, the online format may have lowered search costs by enabling families to access information on laptops, phones, and tablets, rather than relying on the cumbersome, telephone book-sized printed directory. However, this digital shift likely benefited more advantaged families with better access to internet-connected devices. Consistent with this, event studies in Figures A4-A6 show that academic information began influencing the choices of higher-income, Asian, and White families shortly after the launch of SchoolFinder, while impacts for other groups began to emerge one year later. This pattern aligns with findings from other studies on digital access to school information (Cohodes et al., 2022; Hasan & Kumar, 2024; Sattin-Bajaj & Roda, 2018).

Finally, the larger impacts of student satisfaction and academic information in 2018 may reflect greater adoption of the online directory. Although SchoolFinder launched in 2017, it

likely did not become a widely used resource until the following year, when NYCDOE more actively promoted it through printed materials and social media. Correspondingly, Google Trends data (Figures A11 and A12) show a rise in local searches for SchoolFinder from 2017 to 2018, when the district began actively promoting the website.[40] This broader use of the online directory likely boosted the salience and accessibility of student satisfaction and academic information, contributing to the stronger impacts on families' school preferences in 2018.

The absence of an immediate impact from the inclusion of student satisfaction information in the physical directory may have several explanations. One possibility is that families did not view this as new or distinct information. Because the satisfaction measure reflects whether current students believe their school *offers a wide enough variety of programs, classes, and activities*, families may have considered it redundant with existing listings of extracurriculars, clubs, and course offerings already included in the directory. Indeed, this indicator is closely correlated with the number of extracurricular activities, sports, and language courses a school offers (see Figure A13).[41] This suggests that information impacts depend not only on salience but also on whether the information provides substantively new insights. In the next subsection, we explore an additional mechanism that may explain the effects of school information.

7.2.2 Information Architecture

Information format and structure also helps explain information impacts after 2017 when the directory's performance information layout was restructured. Starting in 2017, the physical and online directories presented information in a more concise and digestible format. Specifically, the NYCDOE streamlined school performance profiles from six or more academic indicators to just three key data points on schools' graduation, college enrollment, and attendance rates. This simplified presentation likely reduced *data smog*, decreasing the chances families would misinterpret or overlook academic data and allowing them to more effectively incorporate it into their school choices (Corcoran et al., 2018; Glazerman et al., 2020; Hastings & Weinstein, 2008; Valant & Weixler, 2022).

Furthermore, the design of the SchoolFinder website may help explain the sudden impact of student satisfaction information that year. To simplify searches, the SchoolFinder homepage prominently featured a keyword search box encouraging users to filter schools by

[40] See Appendix B for more details.

[41] The directory provides information on schools' current course offerings and extracurricular programs, which are self-reported by high school administrators to the NYCDOE. Based on each school's directory profile, we count the total number of extracurricular activities and clubs, competitive and club sports, and language offerings available to students.

attributes such as location, extracurricular programs, themes, and courses (e.g., *Try "Chinese"* or *Try "yearbook"*).[42,43] By foregrounding these search options, the site may have nudged families to place greater emphasis on attributes related to student satisfaction.

These search prompts also likely increased families' exposure to schools with higher student satisfaction, as that measure is correlated with the availability of extracurriculars and language courses.[44] To explore this potential mechanism, Figure A14 re-estimates the event study model using the percentiles of the average number of sports, language courses, and extracurricular clubs between 2017 through 2019 as key predictors. Starting in 2018—when the effect of student satisfaction information first became statistically significant—families' choices also became significantly more responsive to these school offerings.

8 Conclusion and Discussion

As policymakers and educators continue to explore strategies for improving educational equity and outcomes, the role of information in shaping families' school choices has gained renewed attention. Our study contributes important causal evidence on how families respond to the provision of non-academic school quality information—specifically, measures of student safety and satisfaction—within the context of a large, urban school district with an established school choice infrastructure.

Our results highlight several key findings. First, we show that schools' non-academic characteristics provide families with information distinct from academic performance measures. Next, we provide causal evidence on how families respond to non-academic school quality information in a large, centralized school choice system. Leveraging a plausibly exogenous shock of non-academic information across New York City, we show that student safety and satisfaction measures meaningfully influence families' ranked school preferences. The effects are both statistically and economically significant—comparable in magnitude or greater than prior estimates of academic value-added information.

Families' responses differed by subgroup. Lower-income families were more responsive to school safety information, suggesting this addressed unmet concerns in their decision-making. In contrast, responses to student satisfaction were similar across income groups.

Importantly, safety information in printed high school directories generated immediate shifts in preferences, while families only significantly reacted to satisfaction measures when the information was delivered online through an interactive website. Two potential mech-

[42] https://web.archive.org/web/20170714113947/http:/schoolfinder.nyc.gov/

[43] https://web.archive.org/web/20170710235902/http:/schoolfinder.nyc.gov/

[44] Figure A13 shows that student satisfaction, and the number of sports, language courses, and clubs offered in NYC schools, explain similar dimensions of schools.

anisms explain these findings. First, by reducing search costs, the NYCDOE's efforts to make non-academic information more salient—via printed directories and, later, an interactive online platform—enabled families to identify schools that better matched their needs. Second, the design of the online directory itself likely helped guide attention toward features like student satisfaction, which gained traction only after the online tool's release.

Our findings suggest that families value the type of non-academic school quality indicators mandated for public reporting under the Every Student Succeeds Act. As more districts publish holistic school quality metrics, our results suggest that investments in information design and delivery can significantly shape families' educational opportunities. Making data accessible, interpretable, and salient—especially for underserved families—may be a powerful lever for improving match quality in school choice systems and reducing barriers to access.

References

Abdulkadiroğlu, A., Pathak, P. A., Schellenberg, J., & Walters, C. R. (2020). Do Parents Value School Effectiveness? *American Economic Review*, *110*(5), 1502–1539. https://doi.org/10.1257/aer.20172040

Ainsworth, R., Dehejia, R., Pop-Eleches, C., & Urquiola, M. (2023). Why Do Households Leave School Value Added on the Table? The Roles of Information and Preferences. *American Economic Review*, *113*(4), 1049–1082. https://doi.org/10.1257/aer.20210949

Angrist, J., Hull, P., Legate-Yang, R., Pathak, P. A., & Walters, C. R. (2025, March). Putting School Surveys to the Test. https://doi.org/10.3386/w33622

Beuermann, D. W., Jackson, C. K., Navarro-Sola, L., & Pardo, F. (2023). What is a Good School, and Can Parents Tell? Evidence on the Multidimensionality of School Output. *The Review of Economic Studies*. https://doi.org/10.1093/restud/rdac025

Billingham, C. M., & Hunt, M. O. (2016). School Racial Composition and Parental Choice: New Evidence on the Preferences of White Parents in the United States. *Sociology of Education*, *89*(2), 99–117. https://doi.org/10.1177/0038040716635718

Bordalo, P., Gennaioli, N., & Shleifer, A. (2022). Salience [_eprint: https://doi.org/10.1146/annurev-economics-051520-011616]. *Annual Review of Economics*, *14*(1), 521–544. https://doi.org/10.1146/annurev-economics-051520-011616

Bruch, E. E., & Mare, R. D. (2012). Methodological Issues in the Analysis of Residential Preferences, Residential Mobility, and Neighborhood Change. *Sociological Methodology*, *42*(1), 103–154. Retrieved September 8, 2021, from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3591474/

Burdick-Will, J., Gebo, L., & Williams, A. D. (2024). Anywhere but Here: Neighborhood Violence and Local School Preferences in Baltimore City [Publisher: SAGE Publications Inc]. *Sociology of Education*, *97*(1), 1–20. https://doi.org/10.1177/00380407231197394

Burdick-Will, J., Nerenberg, K. M., Grigg, J. A., & Connolly, F. (2021). Student Mobility and Violent Crime Exposure at Baltimore City Public Elementary Schools [Publisher: American Educational Research Association]. *American Educational Research Journal*, *58*(3), 602–634. https://doi.org/10.3102/0002831220963908

Campos, C. (2024). Social Interactions, Information, and Preferences for Schools: Experimental Evidence from Los Angeles. *Working Paper*.

Carrell, S. E., Hoekstra, M., & Kuka, E. (2018). The Long-Run Effects of Disruptive Peers. *American Economic Review*, *108*(11), 3377–3415. https://doi.org/10.1257/aer.20160763

Carrell, S. E., & Hoekstra, M. L. (2010). Externalities in the Classroom: How Children Exposed to Domestic Violence Affect Everyone's Kids. *American Economic Journal: Applied Economics*, *2*(1), 211–228. https://doi.org/10.1257/app.2.1.211

Clapp, J. M., Nanda, A., & Ross, S. L. (2008). Which school attributes matter? The influence of school district performance and demographic composition on property values. *Journal of Urban Economics*, *63*(2), 451–466. https://doi.org/10.1016/j.jue.2007.03.004

Cohen, J., McCabe, L., Michelli, N. M., & Pickeral, T. (2008). School Climate: Research, Policy, Practice, and Teacher Education. *Teachers College Record*, 180–213. Retrieved September 10, 2021, from https://www.tcrecord.org/books/exec.asp?ContentID=15220

Cohodes, S., Corcoran, S., Jennings, J., & Sattin-Bajaj, C. (2022). When Do Informational Interventions Work? Experimental Evidence from New York City High School Choice. *NBER Working Paper Series*, 58.

Collins, C. A., & Kaplan, E. K. (2022). Demand for School Quality and Local District Administration. *Economics of Education Review*, *88*, 102252. https://doi.org/10.1016/j.econedurev.2022.102252

Corcoran, S. P., Jennings, J. L., Cohodes, S. R., & Sattin-Bajaj, C. (2018). Leveling the Playing Field for High School Choice: Results from a Field Experiment of Informational Interventions. *NBER Working Paper*. Retrieved September 15, 2022, from https://www-nber-org.proxy.library.cornell.edu/system/files/working_papers/w24471/w24471.pdf

Cornell, D. G., Mayer, M. J., & Sulkowski, M. L. (2021). History and Future of School Safety Research [Publisher: Routledge _eprint: https://doi.org/10.1080/2372966X.2020.1857212]. *School Psychology Review*, *50*(2-3), 143–157. https://doi.org/10.1080/2372966X.2020.1857212

Corradini, V. (2024). Information and Access in School Choice Systems: Evidence from New York City.

Cotman, A., Curran, F. C., & Harris-Walls, K. (2024). Examination of state-level school safety data dashboard characteristics. *Education Policy Analysis Archives*, *32*. https://doi.org/10.14507/epaa.32.8559

Crespin, R. (2025). The Value of School Social Climate Information: Evidence from Chicago Housing Transactions. *Working Paper*.

Davis, J. R., & Warner, N. (2018). Schools Matter: The Positive Relationship Between New York City High Schools' Student Academic Progress and School Climate [Publisher: SAGE Publications Inc]. *Urban Education*, *53*(8), 959–980. https://doi.org/10.1177/0042085915613544

Debs, M., Kafka, J., Makris, M. V., & Roda, A. (2023). Happiness-Oriented Parents: An Alternative Perspective on Privilege and Choosing Schools [Publisher: The University of Chicago Press]. *American Journal of Education*, *129*(2), 145–176. https://doi.org/10.1086/723066

Denice, P., & Gross, B. (2016). Choice, Preferences, and Constraints: Evidence from Public School Applications in Denver [Publisher: SAGE Publications Inc]. *Sociology of Education*, *89*(4), 300–320. https://doi.org/10.1177/0038040716664395

Disare, M. (2016). Education department launches interactive high school directory. *Chalkbeat*. Retrieved January 15, 2025, from https://www.chalkbeat.org/newyork/2016/9/12/21099020/exclusive-education-department-launches-interactive-high-school-directory/

Edwards, E. C. (2021). Centering Race to Move Towards an Intersectional Ecological Framework for Defining School Safety for Black Students [Publisher: Routledge _eprint: https://doi.org/10.1080/2372966X.2021.1930580]. *School Psychology Review*, *50*(2-3), 254–273. https://doi.org/10.1080/2372966X.2021.1930580

Erwin, B., Francies, C., Pechota, D., & McCann, M. (2021, December). *50-State Comparison: States' School Accountability Systems 2021 (archive)* (tech. rep.). Education Commission of the States. Retrieved January 14, 2025, from https://www.ecs.org/50-state-comparison-states-school-accountability-systems-2021-archive/

Friedman, M. (1962). *Capitalism and freedom* [OCLC: 168498]. University of Chicago Press. Retrieved May 20, 2025, from http://catdir.loc.gov/catdir/richcat/toc0701/62019619.html

Gibbons, S., & Silva, O. (2011). School quality, child wellbeing and parents' satisfaction. *Economics of Education Review*, *30*(2), 312–331. https://doi.org/10.1016/j.econedurev.2010.11.001

Glazerman, S., Nichols-Barrer, I., Valant, J., Chandler, J., & Burnett, A. (2020). The Choice Architecture of School Choice Websites. *Journal of Research on Educational Effectiveness*, *13*(2), 322–350. https://doi.org/10.1080/19345747.2020.1716905

Goyette, K. (2014). Setting the Context. In K. Goyette & A. Lareau (Eds.), *Choosing Homes, Choosing Schools* (pp. 1–24). Russell Sage Foundation. Retrieved September 8, 2021, from http://www.jstor.org/stable/10.7758/9781610448208.6

Hailey, C. (2022a). Racial Preferences for Schools: Evidence from an Experiment with White, Black, Latinx, and Asian Parents and Students. *Sociology of Education*, *95*(2), 110–132. https://doi.org/10.1177/00380407211065179

Hailey, C. (2022b). Racialized Perceptions of Anticipated School Belonging [Publisher: SAGE Publications Inc]. *Educational Policy*, *36*(4), 879–910. https://doi.org/10.1177/08959048221087211

Hailey, C. (2025). Choosing Schools, Choosing Safety: How Multiple Dimensions of Safety Shape School Choices. *AERA Open*, *11*(1), 1–19.

Hamlin, D. (2021). Can a Positive School Climate Promote Student Attendance? Evidence From New York City [Publisher: American Educational Research Association]. *American Educational Research Journal*, *58*(2), 315–342. https://doi.org/10.3102/0002831220924037

Harris, D. N., & Larsen, M. F. (2023). What Schools Do Families Want (and Why)? Evidence on Revealed Preferences From New Orleans [Publisher: American Educational Research Association]. *Educational Evaluation and Policy Analysis*, *45*(3), 496–519. https://doi.org/10.3102/01623737221134528

Hasan, S., & Kumar, A. (2024). Who Captures the Value from Organizational Ratings?: Evidence from Public Schools [Publisher: INFORMS]. *Strategy Science*, *9*(3), 248–266. https://doi.org/10.1287/stsc.2023.0113

Hassan, M., & Geys, B. (2016). What Do We Value Most in Schools? A Study of Preference Rankings of School Attributes. *Social Science Quarterly*, *98*(5), 1313–1327. https://doi.org/10.1111/ssqu.12337

Hastings, J. S., Van Weelden, R., & Weinstein, J. (2007, March). Preferences, Information, and Parental Choice Behavior in Public School Choice. https://doi.org/10.3386/w12995

Hastings, J. S., & Weinstein, J. M. (2008). Information, School Choice, and Academic Achievement: Evidence from Two Experiments. *The Quarterly Journal of Economics*, *123*(4), 1373–1414. https://doi.org/10.1162/qjec.2008.123.4.1373

Hoxby, C. M. (2003). School choice and school competition: Evidence from the United States. *Swedish Economic Policy Review*.

Huebner, E. S. (1994). Preliminary development and validation of a multidimensional life satisfaction scale for children [Place: US Publisher: American Psychological Association]. *Psychological Assessment*, *6*(2), 149–158. https://doi.org/10.1037/1040-3590.6.2.149

Huebner, E. S., & Gilman, R. (2006). Students Who Like and Dislike School [Company: Springer Distributor: Springer Institution: Springer Label: Springer Number: 2 Publisher: Kluwer Academic Publishers]. *Applied Research in Quality of Life*, *1*(2), 139–150. https://doi.org/10.1007/s11482-006-9001-3

Idoux, C. M., & Corradini, V. (2024). Overcoming Racial Gaps in School Preferences: The Effect of Peer Diversity on School Choice. *NBER Working Paper*.

Imberman, S. A., & Lovenheim, M. F. (2016). Does the market value value-added? Evidence from housing prices after a public release of school and teacher value-added. *Journal of Urban Economics*, *91*, 104–121. https://doi.org/10.1016/j.jue.2015.06.001

Jacob, B. A., & Lefgren, L. (2007). What Do Parents Value in Education? An Empirical Investigation of Parents' Revealed Preferences for Teachers. *The Quarterly Journal of Economics*, *122*(4), 1603–1637. https://doi.org/10.1162/qjec.2007.122.4.1603

Jennings, K. (2011, March). Welcome to the Safe and Supportive Schools Website. Retrieved September 13, 2021, from https://web.archive.org/web/20110316080654/http://safesupportiveschools.ed.gov/index.php?id=7&pid=1

Jordan, P., & Hamilton, L. (2019, December). *Walking a Fine Line: School Climate Surveys in State ESSA Plans* (tech. rep.). FutureEd - Georgetown University. Retrieved August 30, 2021, from https://www.future-ed.org/wp-content/uploads/2019/12/FutureEdSchoolClimateReport.pdf

Lacoe, J. (2020). Too Scared to Learn? The Academic Consequences of Feeling Unsafe in the Classroom [Publisher: SAGE Publications Inc]. *Urban Education*, *55*(10), 1385–1418. https://doi.org/10.1177/0042085916674059

Nathanson, L., McCormick, M., Kemple, J. J., & Sypek, L. (2013). Strengthening Assessments of School Climate:

NYC DOE. (2023). NYC School Survey Archives. Retrieved January 16, 2025, from https://infohub.nyced.org/reports/students-and-schools/school-quality/nyc-school-survey/survey-archives

Parker, J. A., & Souleles, N. S. (2017, October). *Reported Effects vs. Revealed-Preference Estimates: Evidence from the propensity to spend tax rebates* (Working Paper No. 23920) (Series: Working Paper Series). National Bureau of Economic Research. https://doi.org/10.3386/w23920

Porter, S. C., Jackson, C. K., Kiguel, S., & Easton, J. Q. (2023). High School Climate and Organizational Context Shape Student Development and Educational Attainment.

Rachkovski, G. (2025). Beyond Test Scores: Does Public Information on School Satisfaction and Violence Levels Affect Parental School Choice? *SSRN Working Paper*. https://papers.ssrn.com/abstract=5233765

Rhodes, A., & DeLuca, S. (2014). Residential Mobility and School Choice Among Poor Families. In *Choosing Homes, Choosing Schools* (pp. 137–166). Russell Sage Foundation. Retrieved May 19, 2025, from http://www.jstor.org/stable/10.7758/9781610448208.10

Rich, P. M., & Jennings, J. L. (2015). Choice, Information, and Constrained Options: School Transfers in a Stratified Educational System. *American Sociological Review*, *80*(8), 1069–1098. https://doi.org/10.1177/0003122415598764

Sattin-Bajaj, C. (2014, September). *Unaccompanied Minors: Immigrant Youth, School Choice, and the Pursuit of Equity*. Retrieved May 19, 2025, from https://hep.gse.harvard.edu/9781612507095/unaccompanied-minors/

Sattin-Bajaj, C., Jennings, J. L., Corcoran, S. P., Baker-Smith, E. C., & Hailey, C. (2018). Surviving at the Street Level: How Counselors' Implementation of School Choice Policy Shapes Students' High School Destinations. *Sociology of Education*, *91*(1), 46–71. https://doi.org/10.1177/0038040717751443

Sattin-Bajaj, C., & Roda, A. (2018). Opportunity Hoarding in School Choice Contexts: The Role of Policy Design in Promoting Middle-Class Parents' Exclusionary Behaviors. *Educational Policy*. Retrieved January 23, 2025, from https://journals.sagepub.com/doi/full/10.1177/0895904818802106

Suldo, S. M., Gilfix, H. L., & Morgan, M. M. (2022). Understanding and Promoting School Satisfaction in Children and Adolescents [Num Pages: 17]. In *Handbook of Positive Psychology in Schools* (3rd ed.). Routledge.

Thapa, A., Cohen, J., Guffey, S., & Higgins-D'Alessandro, A. (2013). A Review of School Climate Research. *Review of Educational Research*, *83*(3), 357–385. https://doi.org/10.3102/0034654313483907

U.S. Department of Education. (2013, February). Topics & Research: Topics and Research. Retrieved September 13, 2021, from https://web.archive.org/web/20130215154301/http:/safesupportiveschools.ed.gov/index.php?id=33

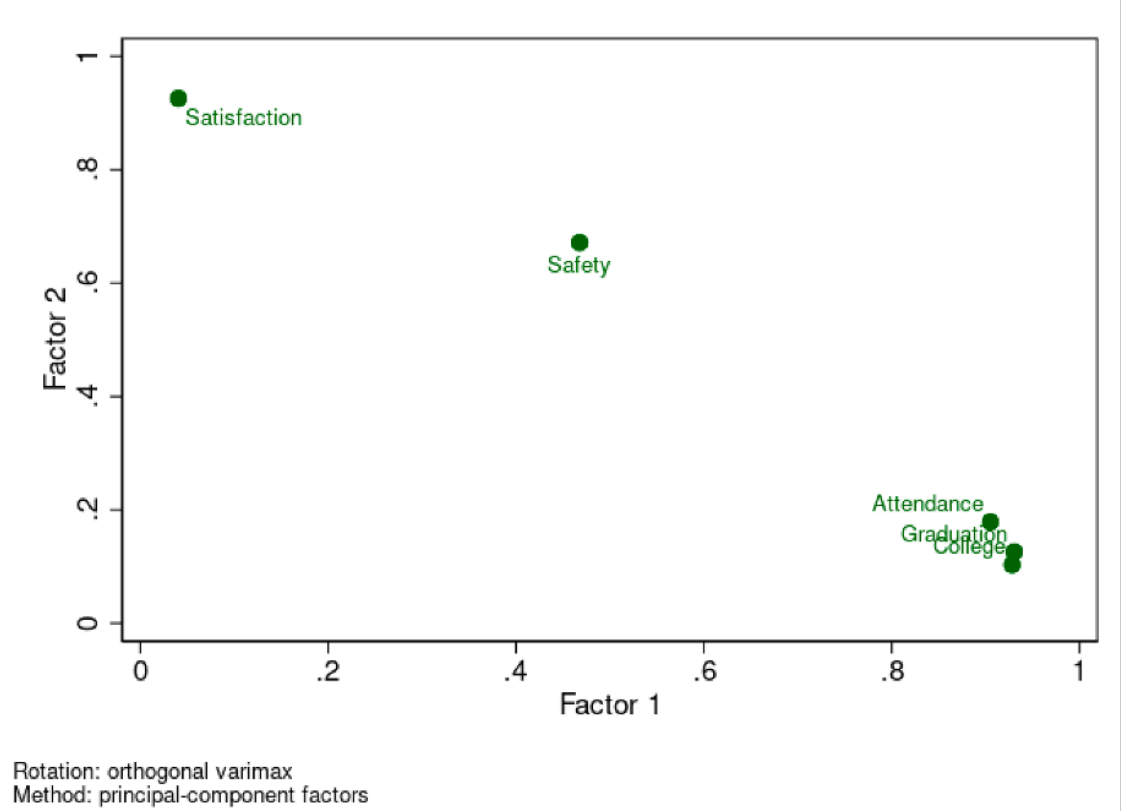
Valant, J., & Weixler, L. H. (2022). Informing School-Choosing Families About Their Options: A Field Experiment From New Orleans [Publisher: American Educational Research Association]. *Educational Evaluation and Policy Analysis*, *44*(4), 608–637. https://doi.org/10.3102/01623737221086305

Wada, R., & Zahirovic-Herbert, V. (2013). Distribution of Demand for School Quality: Evidence from Quantile Regression [Num Pages: 15 Place: Washington, United Kingdom Publisher: Taylor & Francis Ltd.]. *Journal of Housing Research*, *22*(1), 17–31. Retrieved July 26, 2024, from https://www.proquest.com/docview/1353322713/abstract/4C76028391684FCEPQ/1

Warikoo, N. (2024, May). *Race at the Top: Asian Americans and Whites in Pursuit of the American Dream in Suburban Schools*. University of Chicago Press. Retrieved May 16, 2025, from https://press.uchicago.edu/ucp/books/book/chicago/R/bo149570065.html

Figures

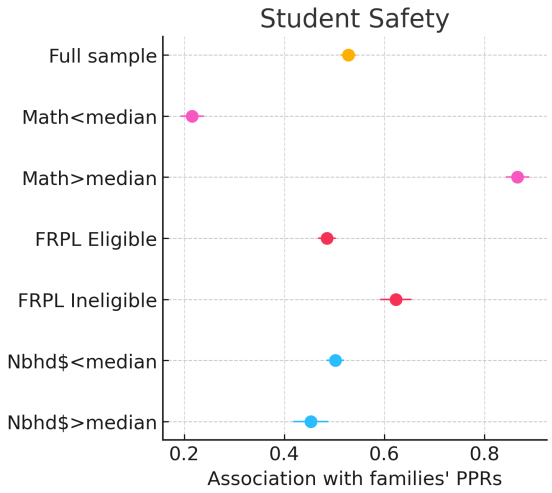
Figure 1: Unrotated Factor Loadings Plot



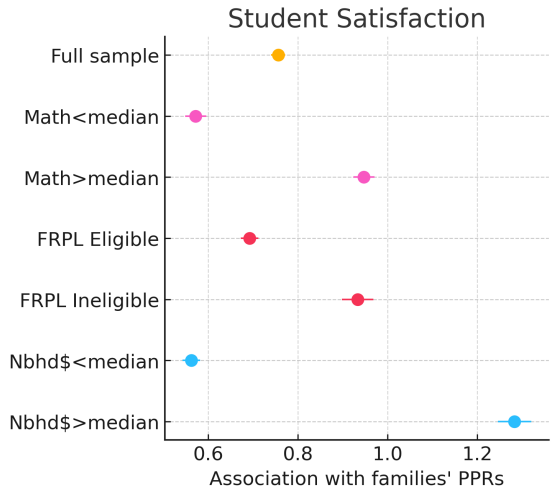
Notes: The analysis uses actual data of five school characteristics, based on years 2012 through 2015. Principal component analysis conducted using *factor* command in Stata with the pcf option, which is then followed by *rotate*, and lastly by *loadingplot*.

Figure 2: Associations between families' preference percentile rankings and school characteristics

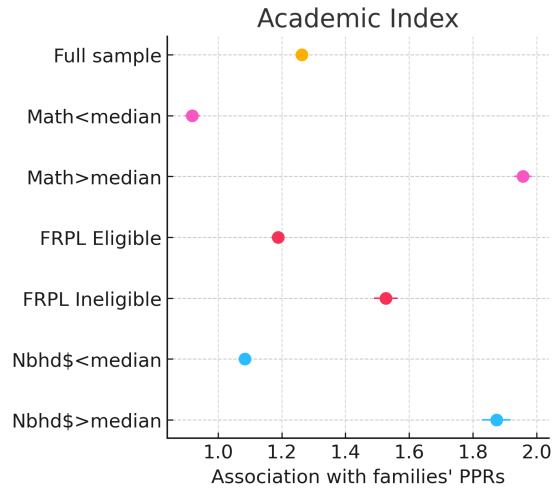
(a) Student Safety, by math/income



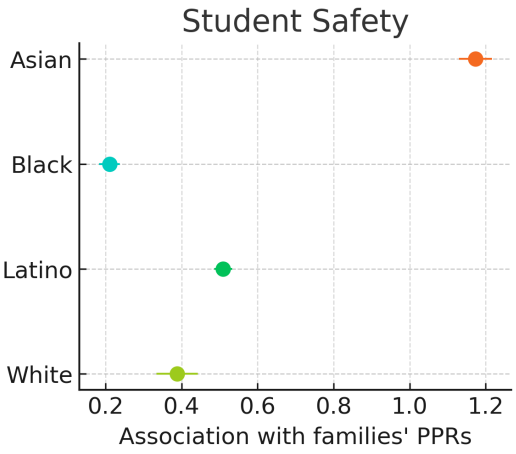
(b) Student Satisfaction, by math/income



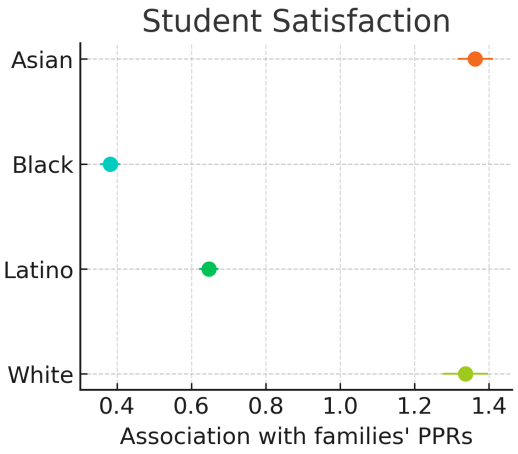
(c) Academic Index, by math/income



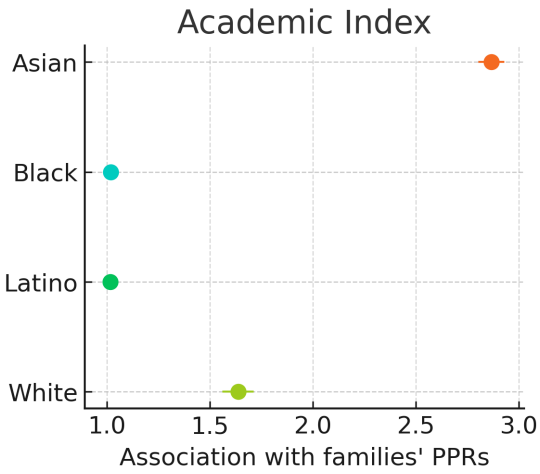
(d) Student Safety, by race



(e) Student Satisfaction, by race

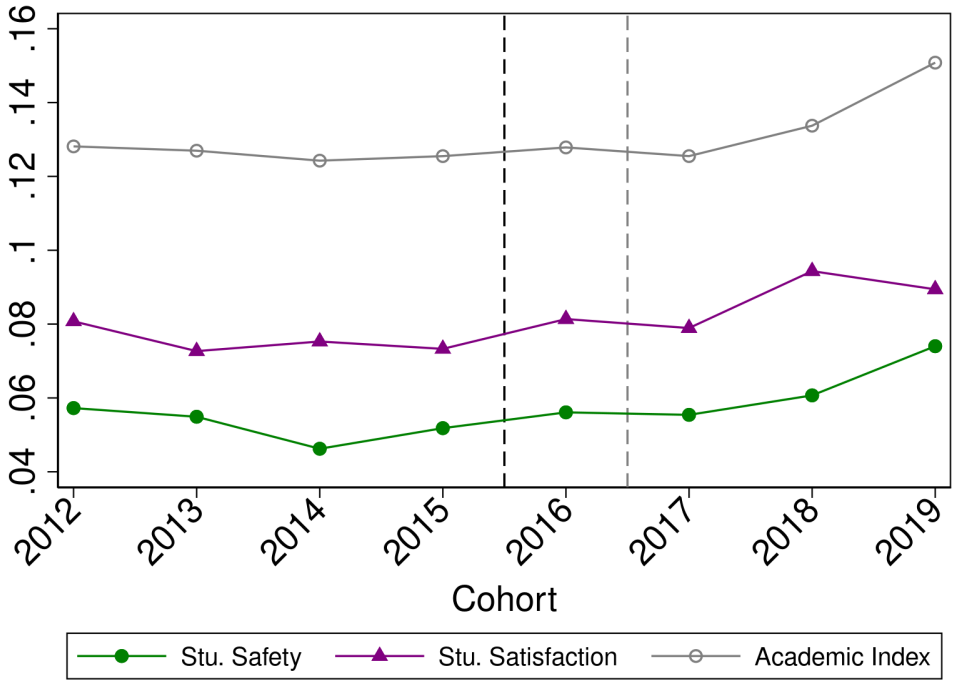


(f) Academic Index, by race



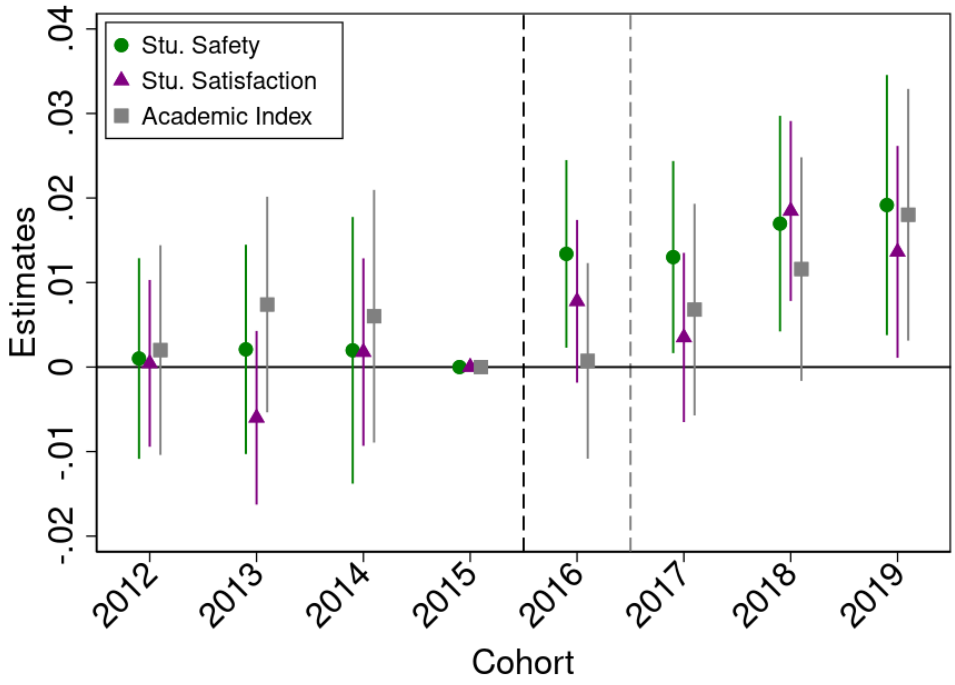
Note: Estimates are multiplied by 10 for ease of presentation. The outcome of interest is families' preference percentile ranking of a school, while the regressor is the percentile for each school characteristic (based on information from the 2016 to 2017 average). 95% Confidence Interval bands are based on standard errors clustered at the student-by-year level.

Figure 3: Associations Between Families' PPRs and School Characteristics



Notes: This figure presents raw trends of the associations between families' preference percentile rankings (PPR) and the post-shock average for each of the school characteristics (based on information from the 2016 to 2017 average). Each point estimate presents the association between PPR and each of the three school characteristics by conducting separate bivariate regressions for each cohort. The vertical dashed black line marks the start of the non-academic information shock in the high school directory, while the vertical dashed gray line symbolizes the beginning of the online high school directory.

Figure 4: Impacts of Directory Information Shocks on Families' Preference Percentile Rank



Notes: Event study is based on equation 2, where estimates come from a single regression. The black vertical dashed line separates the periods before/after the release of the students safety and satisfaction information. The gray vertical dashed line shows when the interactive online High School Directory was first released.

Tables

Table 1: Summary Statistics

Variable	Mean	Std. Dev.
Panel A: Families' Preference Percentile Ranks		
Preference Percentile Rank (PPR)	0.59	0.29
Panel B: School Characteristics in Percentile Ranks		
Student Safety	0.49	0.29
Student Satisfaction	0.50	0.29
Academic Index	0.49	0.28
Panel C: School Characteristics in Average Percentage		
Student Safety (%)	82.24	8.63
Student Satisfaction (%)	74.30	11.84
Graduation Rate (%)	74.12	15.02
College Enrollment Rate (%)	54.54	18.13
Attendance Rate (%)	87.07	5.58
Panel D: Applicant Demographics		
Subsidized-Lunch Eligible	0.75	0.43
Avg. Zip-Code Income ($1,000s)	52.66	48.69
Asian	0.15	0.36
Black	0.29	0.45
Latino	0.43	0.49
White	0.13	0.34
N – student-by-ranked-school	2,500,601	
N – unique students-by-cohort	437,764	
N – schools	339	

Notes: Summary statistics are calculated from the analytic sample described in Section 2. The academic and non-academic characteristics are based on data from the 2016-2017 averages. Panel A is calculated based on all observations in the sample. The PPR average leans to the right of the 50th percentile, because PPR ranges from 0.083 to 1, which excludes the value of zero. Panels B and C are calculated based on unique school observations, and Panel D is based on unique student-by-cohort observations. Standard deviations are reported alongside means.

Table 2: Correlation matrix of school characteristics (pre-shock period)

	(1)	(2)	(3)	(4)	(5)
(1) Average SAT	1.00				
(2) Academic Index	0.74	1.00			
(3) Student Safety	0.34	0.51	1.00		
(4) Student Satisfaction	0.12	0.24	0.47	1.00	
(5) School Impacts	0.00	0.33	0.36	0.14	1.00

Notes: Sample is based on pre-shock period (2012-2015), with dependent and independent variables from the same year, except for school impacts which are from 2015 as described in the data section. Academic index is based on factor analysis of graduation rates, college enrollment rates, and attendance rates.

Table 3: Predictability of academic and non-academic school characteristics (pre-shock period)

	(1) Average SAT	(2) Academic Index	(3) Student Safety	(4) Student Satisfaction	(5) School Impacts
Observations	1,220	1,220	1,220	1,220	1,220
R-squared	0.841	0.780	0.440	0.220	0.222
Adjusted R-squared	0.839	0.778	0.433	0.211	0.214

Notes: Sample is based on pre-shock period (2012-2015), with dependent and independent variables from the same year, except for school impacts which are from 2015 as described in the data section. All factors are in percentiles for comparability. Academic index is based on factor analysis of graduation rates, college enrollment rates, and attendance rates. These models control for the average SAT score (except in column 1), the academic index (except in column 2), and NYC's measure of school impacts/value-added (except in column 5). The regressions also include controls for incoming 8th-grade proficiency, poverty rates, racial composition, and the shares of English Language Learners, and students with disabilities.

Table 4: Associations between families' PPRs and school characteristics (pre-shock period)

	(1) PPR	(2) PPR	(3) PPR
Student Safety	0.528***		
	(0.008)		
Student Satisfaction		0.756***	
		(0.008)	
Academic Index			1.263***
			(0.009)
Observations	1,302,171	1,302,171	1,302,171

Note: Estimates are multiplied by 10 for ease of presentation. The outcome of interest is families' preference percentile ranking of a school, while the regressor is the percentile rank for each school characteristic among all other NYC schools (based on information from the 2016 to 2017 average). Standard errors (in parentheses) are clustered at the student-by-year level.

Table 5: Information Impacts on Families' Preference Percentile Rankings (PPRs)

	Overall Info Shock		Separate Info Shocks (Physical + Online)	
	(1)	(2)	(3)	(4)
Stu. Safety$_{initial}$ × (t≥2016)	0.134***	0.141***	0.113***	0.113***
	(0.035)	(0.035)	(0.041)	(0.042)
	[25.4%]	[26.7%]	[21.4%]	[21.4%]
Stu. Satisfaction$_{initial}$ × (t≥2016)	0.117***	0.118***	0.035	0.037
	(0.030)	(0.031)	(0.038)	(0.038)
	[15.5%]	[15.6%]	[4.6%]	[4.9%]
Academic Index$_{initial}$ × (t≥2016)	0.046	0.055	−0.036	−0.029
	(0.035)	(0.035)	(0.041)	(0.041)
	[3.6%]	[4.4%]	[−2.9%]	[−2.3%]
Stu. Safety$_{2017–2019}$ × (t≥2017)			0.035	0.039
			(0.045)	(0.046)
			[6.6%]	[7.4%]
Stu. Satisfaction$_{2017–2019}$ × (t≥2017)			0.099**	0.100**
			(0.039)	(0.040)
			[13.1%]	[13.2%]
Academic Index$_{2017–2019}$ × (t≥2017)			0.121**	0.130***
			(0.047)	(0.048)
			[9.6%]	[10.3%]
$ln(distance)$		−0.035***		−0.035***
		(0.001)		(0.001)
Observations	2,408,462	2,408,462	2,408,462	2,408,462

Notes: Information impact estimates are multiplied by 10 for ease of presentation. Estimation in columns (1) and (2) based on equation 1, where the initial information shocks are based on the 2016 to 2017 average for each school characteristic. Estimates in columns (3) and (4) are based on equation 3, where the initial information shocks are based on the 2016's directory information for each characteristic. Percent impacts (in brackets) are calculated by dividing the DID estimate by the corresponding pre-shock period association. Standard errors are clustered at the school-by-year level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Heterogeneity in Information Impacts on Families' Preference Percentile Rankings (PPRs)

	By Incoming Math Score		By Subsidized Lunch		By Neighborhood Income		By Race/Ethnicity			
	Below Median	Above Median	Eligible	Ineligible	Below Median	Above Median	Asian	Black	Latino	White
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Safety×(t≥2016)	0.141***	0.145***	0.150***	0.096*	0.186***	-0.084	0.221**	0.072*	0.203***	-0.029
	(0.035)	(0.052)	(0.036)	(0.053)	(0.034)	(0.075)	(0.094)	(0.042)	(0.038)	(0.096)
	[65.3%]	[16.7%]	[30.9%]	[15.4%]	[37.1%]	[-18.5%]	[18.8%]	[34.3%]	[39.9%]	[-7.5%]
Satis.×(t≥2016)	0.092***	0.147***	0.112***	0.142***	0.099***	0.161***	0.155**	0.083**	0.120***	0.216***
	(0.032)	(0.042)	(0.031)	(0.045)	(0.032)	(0.052)	(0.065)	(0.039)	(0.035)	(0.074)
	[16.1%]	[15.5%]	[16.2%]	[15.2%]	[17.6%]	[12.5%]	[11.4%]	[21.7%]	[18.5%]	[16.2%]
Acad.×(t≥2016)	0.054	0.048	0.034	0.169***	0.034	0.147*	0.008	0.073*	0.031	0.212
	(0.035)	(0.057)	(0.036)	(0.060)	(0.035)	(0.085)	(0.107)	(0.044)	(0.040)	(0.135)
	[5.9%]	[2.5%]	[2.9%]	[11.1%]	[3.1%]	[7.8%]	[0.3%]	[7.2%]	[3.1%]	[13.0%]
$ln(distance)$	-0.035***	-0.035***	-0.035***	-0.038***	-0.033***	-0.041***	-0.037***	-0.027***	-0.037***	-0.054***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Observations	1,198,869	1,175,307	522,488	1,885,974	1,894,774	499,431	338,415	841,932	1,127,657	214,109

Notes: Information impact estimates are multiplied by 10 for ease of presentation. Estimation is based on equation 1, where the information shocks are based on the 2016 to 2017 average for each school characteristic. Percent impacts (in brackets) are calculated by dividing the DID estimate by the corresponding pre-shock period association. Standard errors are clustered at the school-by-year level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix A Figures and Tables

Figure A1: High School Directory page from 2015-16

Eleanor Roosevelt High School • DBN 02M416

Contact Information

Address: 411 East 76th Street
Manhattan, NY 10021
Phone: 212-772-1220
Fax: 212-772-1440
Email: info@erhsnyc.net
Website: www.erhsnyc.org

Building Information

Subway: 6 to 77th St
Bus: BxM1, M101, M102, M15, M15-SBS, M31, M66, M72, M79, M86, M98, Q102
Shared Space: No
Total Students in School: 541
Grade Span of School (2016-2017)**:** 9-12

Student Supports

Site Accessibility: Functionally Accessible
Special Education Services: This school will provide students with disabilities the supports and services indicated on their IEPs.
English Language Learner Programs: ESL

School Life

- Typical 9th Grade Schedule: 8:20 AM – 2:40 PM

Overview

Eleanor Roosevelt High School provides a supportive and rigorous college preparatory environment that places emphasis on giving back to the community. All students take four years of all core subjects and work towards achieving an Advanced Regents diploma.

Academic Opportunities

Program Highlights: Four years of Advisory, English, Math, Science, and Social Studies courses; Wide array of arts options in all grades includes offerings in visual arts, music, and media/technology; Underclassmen take Foundations of Math, Health, Computational Thinking, and Writing Seminar; Upperclassmen have electives available in every subject, including advanced and Advanced Placement (AP) courses.
Language Classes: French, Spanish
Advanced Placement (AP) Courses: Art History, Biology, Calculus, Chemistry, Comparative Government and Politics, Economics, English, Music Theory, Spanish, Statistics, Studio Art, United States History, World History
Diploma Endorsements: Math, Science

Extracurricular Activities and Clubs

Autism Awareness, Canstruction, Chamber Music Society, Chess, Comedy, Dance, Drama, ElRo Ambassadors, ElRo Experiment Science Magazine, ElRo Sibs (Peer Mentoring), Film, Gay-Straight Alliance, Green Team, Investment & Finance, Jazz Ensemble, Law Team, Making a Difference, Math, Model UN, Multicultural Club, National Honor Society, 'Pawprint' Online Newspaper, Speech & Debate, Student Government, Student Movement Against Cancer (SMAC), Students for Sensible Gun Laws, Technology Volunteers, UNICEF, Women's Equality
PSAL Sports - Boys: Baseball, Basketball, Football, Outdoor Track, Soccer, Tennis
PSAL Sports - Girls: Basketball, Flag Football, Soccer, Softball, Tennis, Volleyball
School Sports: Cross Country and Golf

School Performance

	What % of Students...		Quality Review (2014-2015)
	Graduate in 4 years?	Graduate and then enroll in college or career programs?	Curriculum
			Instruction
2013-2014	**100%**	**89%**	Assessing Student Learning
2012-2013	100%	97%	High Expectations
Manhattan Average	70%	53%	Teacher Collaboration

- **94%** of students feel that their school offers enough variety of programs, classes, and activities to keep them interested in school.
- **98%** of students feel safe in the hallways, bathrooms, locker rooms, and cafeteria.

Admissions Priorities and Programs

Admissions Priorities

1. Priority to District 2 students or residents
2. Then to Manhattan students or residents
3. Then to New York City residents

					Prior Year Admissions		
Program Name	**Code**	**Interest Area**	**Admissions Method**	**Grade**	**Seats**	**Applicants**	**Applicants per Seat**
Eleanor Roosevelt High School	M21A	Humanities & Interdisciplinary	Screened	9	125	5376	43 per seat
				10	12	334	28 per seat

Program Description: A program incorporating the arts and technology as essential components of learning.
Selection Criteria - Programs may adjust their selection criteria ranges based on the applicant pool. See p. 7 for more information.

- Course Grades: English (90-100), Math (90-100), Social Studies (90-100), Science (90-100)
- Standardized Test Scores: English Language Arts (3.0-4.5), Math (3.0-4.5)
- Attendance and Punctuality
- Course grade in Language other than English

Notes: High School directory page from 2015-16 for Eleanor Roosevelt High School (02M416).

Figure A2: High School Directory page from 2016-17

Eleanor Roosevelt High School | 02M416

SCHOOL OVERVIEW

Eleanor Roosevelt High School (ElRo) provides a supportive and rigorous college preparatory environment that places emphasis on giving back to the community. All students take four years of all core subjects and work towards achieving an Advanced Regents diploma.

❿ 10th Grade Seats Also Offered

ACADEMICS

- Four years of Advisory, English, Math, Science, and Social Studies courses
- Wide array of arts options in all grades includes offerings in visual arts, music, and media/technology
- Underclassmen take Foundations of Math, Health, Computational Thinking, and Writing Seminar
- Upperclassmen have electives available in every subject, including advanced and Advanced Placement (AP) courses

English Language Learner Programs: English as a New Language

Language Courses: French, Spanish

Advanced Placement (AP) Courses: Art History, Biology, Calculus, Chemistry, Comparative Government and Politics, Economics, English, Music Theory, Statistics, US History, World History

Diploma Endorsements: Math, Science

ACTIVITIES

Construction, Chamber Music, Chess, Dance, Drama, ElRo Ambassadors, ElRo Experiment Science Magazine, ElRo Sibs (Peer Mentors), Film, Gender & Sexuality Alliance, Green Team, Junior Statesmen of America, Investment & Finance, Jazz Ensemble, Law Team, Making a Difference, Math, Model UN, Multicultural Club, NHS, Online Newspaper, Speech & Debate, Student Government, Student Movement Against Cancer, Students for Sensible Gun Laws, Tech Volunteers, UNICEF, Women's Empowerment, Yearbook

PSAL Sports—Boys: Baseball, Basketball, Outdoor Track, Soccer, Tennis

PSAL Sports—Girls: Basketball, Cross Country, Flag Football, Outdoor Track, Soccer, Softball, Tennis, Volleyball

PSAL Sports—Coed: Golf

PERFORMANCE

100% of students graduate in four years

95% of students enroll in college or career programs

97% student attendance

98% of students feel safe in the hallways, bathrooms, locker room, and cafeteria

90% of students feel that this school offers a wide enough variety of programs, classes, and activities to keep them interested in school

Search 02M416 at schools.nyc.gov/accountability for more about this school's performance.

SCHOOL INFORMATION

Neighborhood: Lenox Hill
Address: 411 East 76th Street, Manhattan NY 10021
Site Accessibility: Accessible
Phone: 212-772-1220 • **Fax:** 212-772-1440
Email: info@erhsnyc.net
Website: www.erhsnyc.org
Subway: 6 to 77th St
Bus: BxM1, M101, M102, M103, M15, M15-SBS, M31, M66, M72, M79, M86-SBS, M98, Q102

SCHOOL LIFE

Grade Span: 9-12
Total Students: 554
Typical 9th Grade Schedule: 8:20am-2:40pm

PROGRAM ADMISSIONS

Program Name	Code	Interest Area	Admissions Method	Prior Year Admissions: Type	Seats	Filled	Applicants	Applicants Per Seat	10th Grade Seats Offered
Eleanor Roosevelt High School	**M21A**	Humanities & Interdisciplinary	Screened	GE	104	Y	5,298	51	Yes – 5
				SWD	21	Y	284	14	

Admissions Priorities: ❶ Priority to District 2 students or residents—87% of offers went to this group ❷ Then to Manhattan students or residents ❸ Then to New York City residents

Program Description: A program incorporating the arts and technology as essential components of learning.

Selection Criteria (prior year ranges—learn more in the introduction):

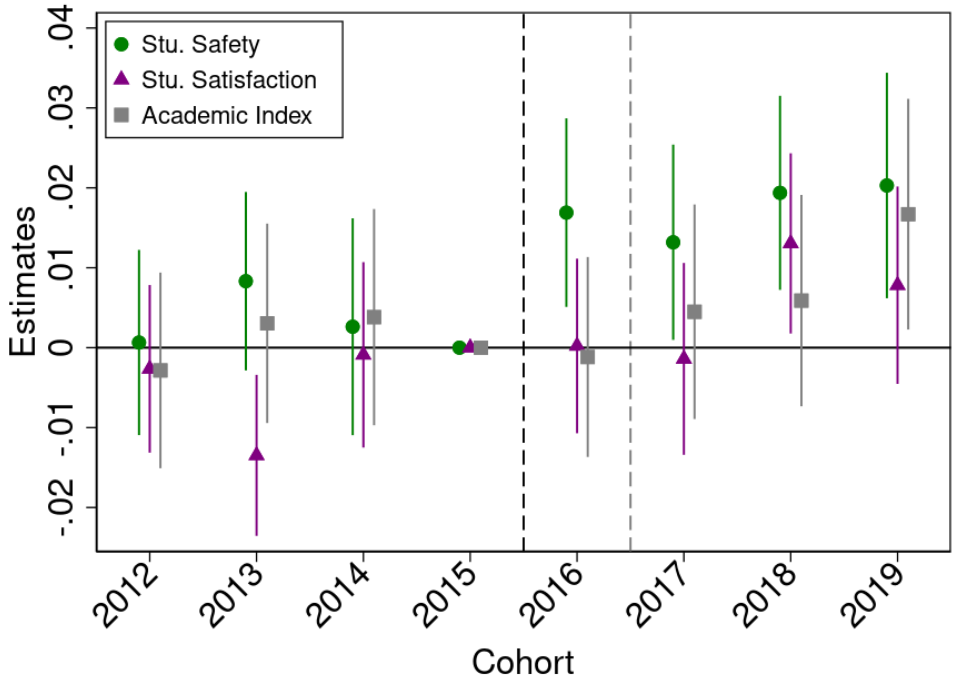
Initial Filter: Attendance

- Course Grades: English (91-100), Math (91-100), Social Studies (92-100), Science (92-100)
- Standardized Test Scores: English Language Arts (3.3-4.5), Math (3.7-4.5)

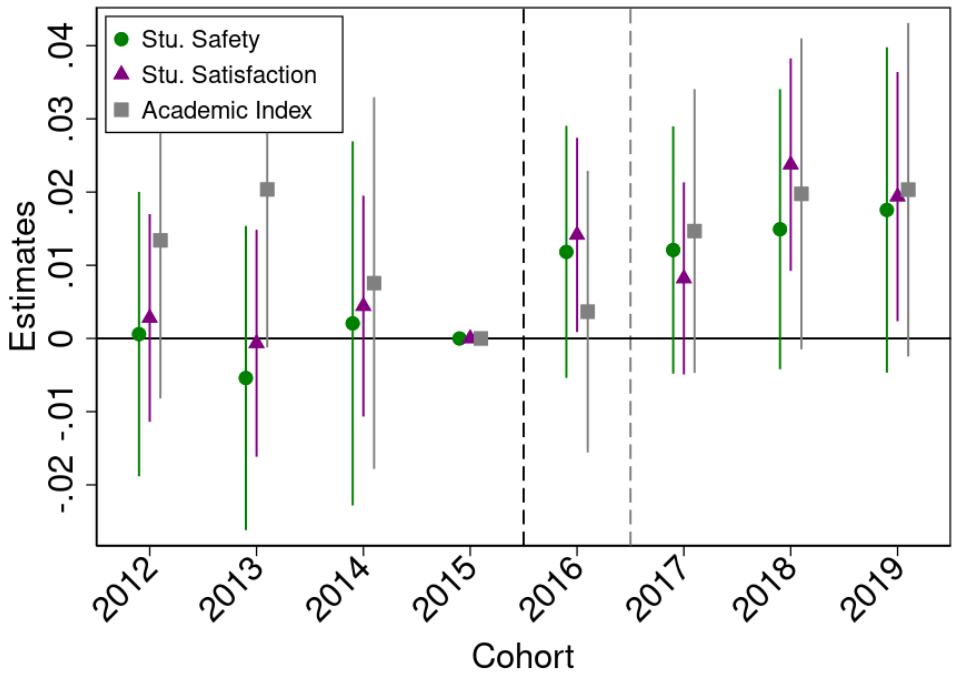
Notes: High School directory page from 2016-17 for Eleanor Roosevelt High School (02M416).

Figure A3: Impacts of Directory Information Shocks on Families' Preference Percentile Rank, by student's incoming math performance

(a) Below median



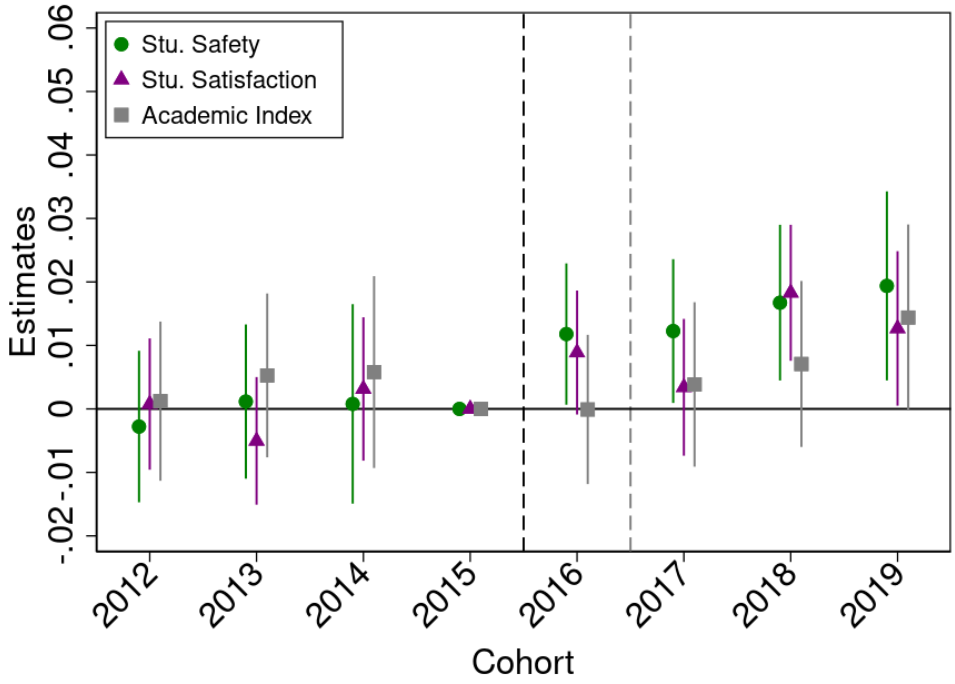
(b) Above median



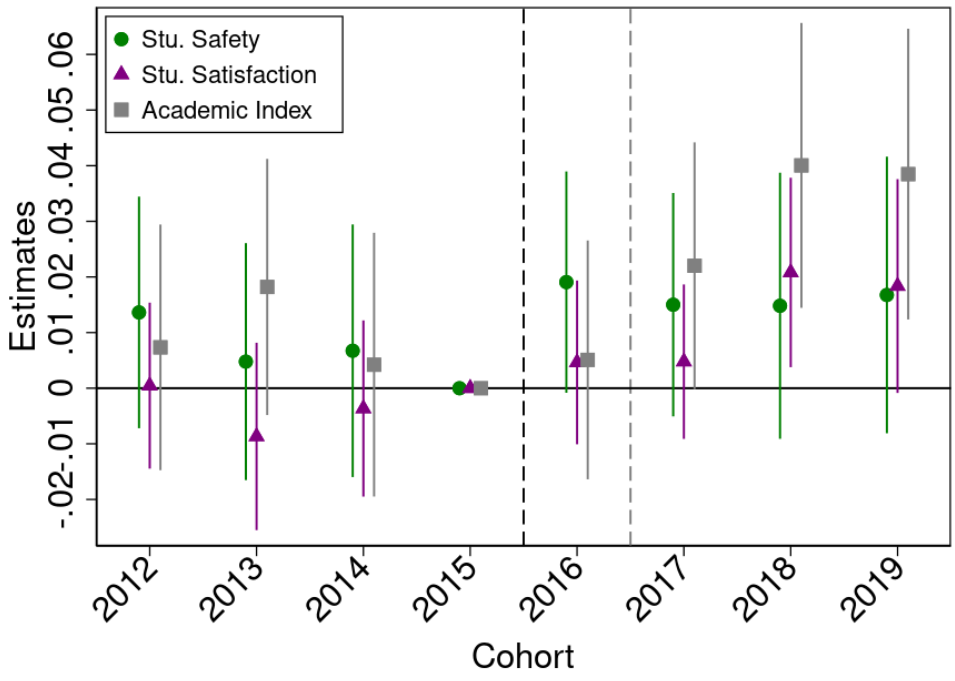
Notes: Event study is based on equation 2, where the only information is based on extracurriculars. The black vertical dashed line separates the periods before/after the release of the students safety and satisfaction information. The red vertical dashed line shows when the interactive online High School Directory was first released.

Figure A4: Impacts of Directory Information Shocks on Families' Preference Percentile Rank, by student's subsidized lunch eligibility

(a) Eligible



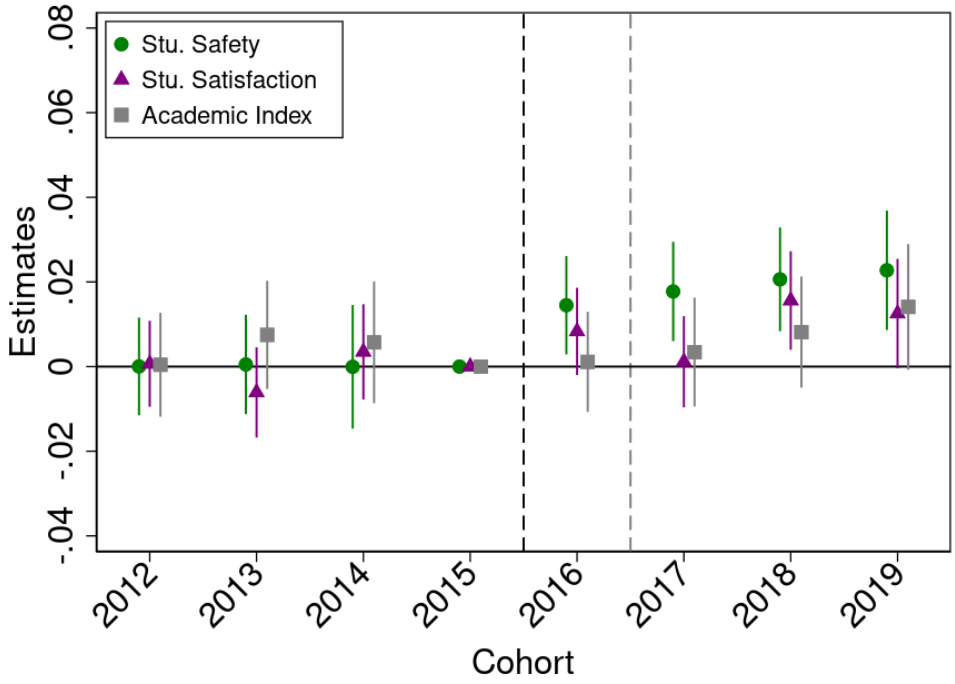
(b) Ineligible



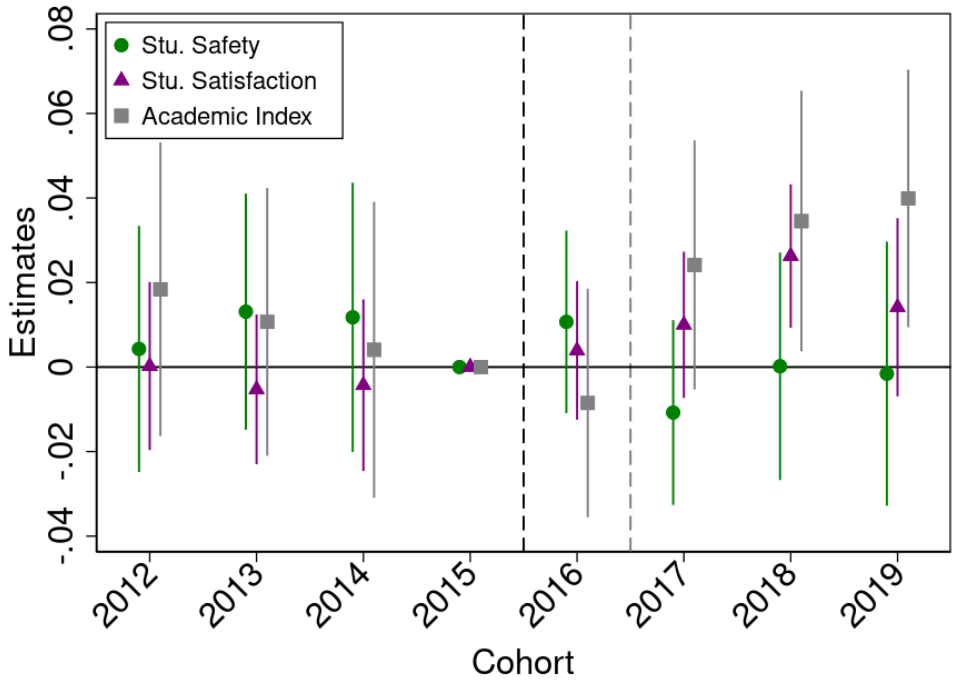
Notes: Event study is based on equation 2, where the only information is based on extracurriculars. The black vertical dashed line separates the periods before/after the release of the students safety and satisfaction information. The red vertical dashed line shows when the interactive online High School Directory was first released.

Figure A5: Impacts of Directory Information Shocks on Families' Preference Percentile Rank, by student's neighborhood income

(a) Below median



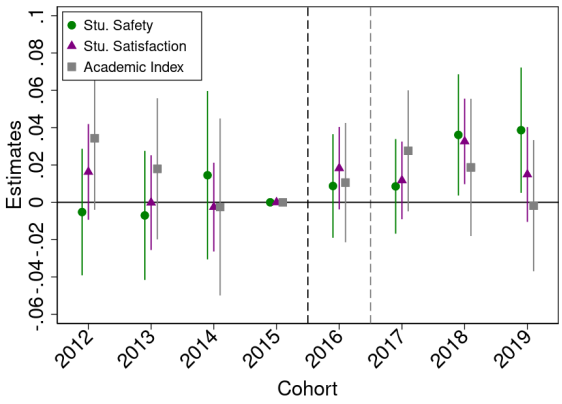
(b) Above median



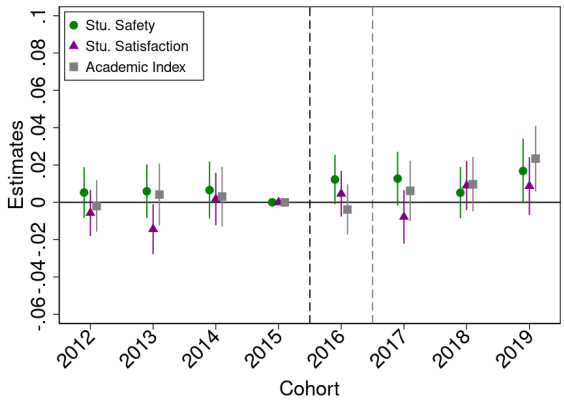
Notes: Event study is based on equation 2, where the only information is based on extracurriculars. The black vertical dashed line separates the periods before/after the release of the students safety and satisfaction information. The red vertical dashed line shows when the interactive online High School Directory was first released.

Figure A6: Impacts of Directory Information Shocks on Families' Preference Percentile Rank, by student's race/ethnicity

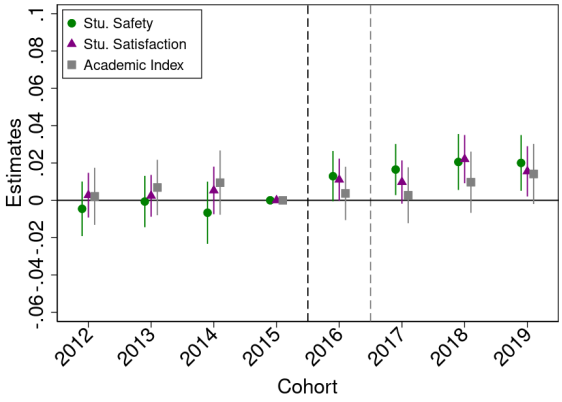
(a) Asian



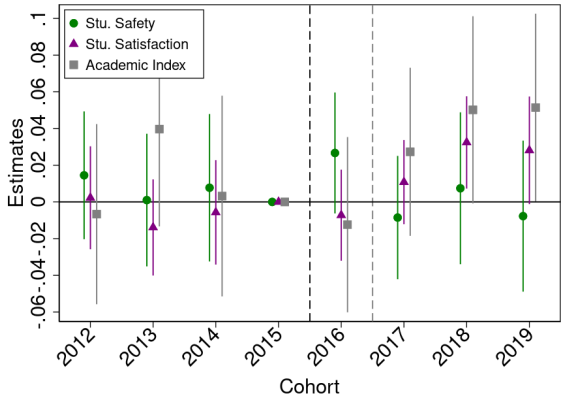
(b) Black



(c) Latino

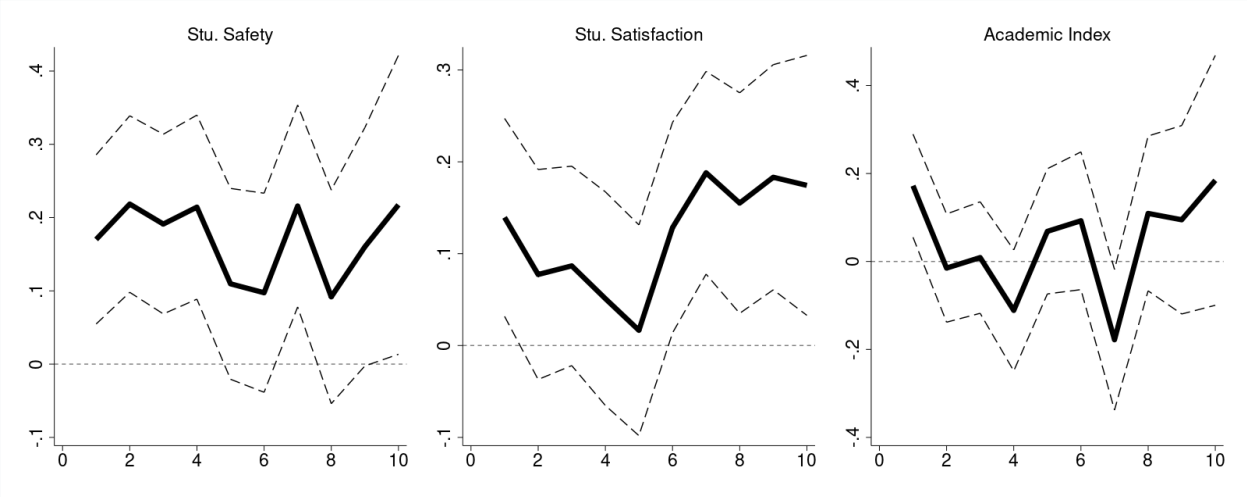


(d) White



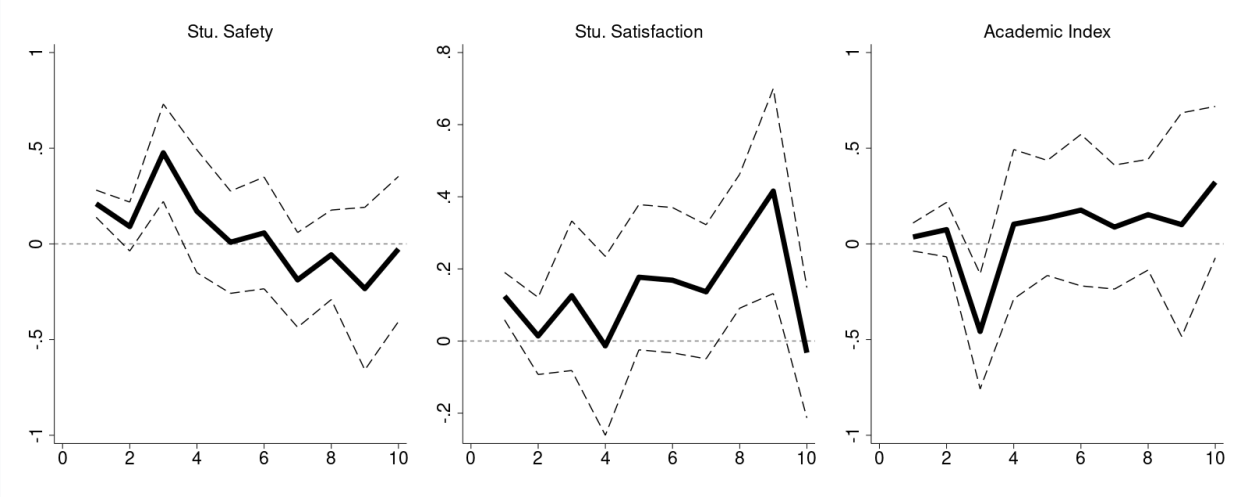
Notes: Event study is based on equation 2, where the only information is based on extracurriculars. The black vertical dashed line separates the periods before/after the release of the students safety and satisfaction information. The red vertical dashed line shows when the interactive online High School Directory was first released.

Figure A7: Overall Information Impacts by Incoming Math Score Decile



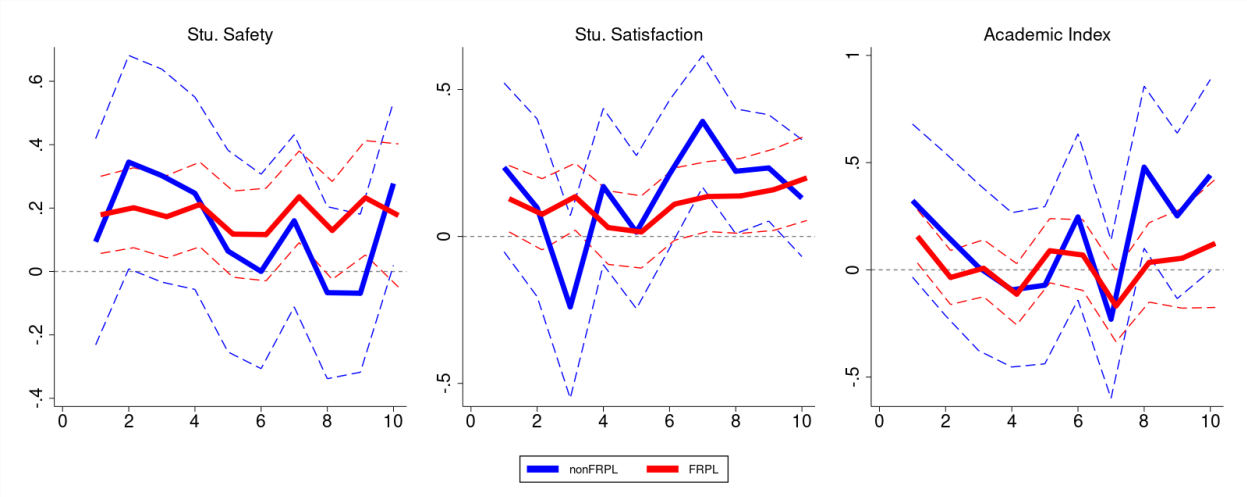
Notes: This figure displays distribution regression estimates, based on equation 1, across students' incoming 8th grade math achievement by deciles. Estimates are multiplied by 10 for ease of presentation. Standard errors are clustered at the school-by-year level.

Figure A8: Overall Information Impacts by Neighborhood Income Decile



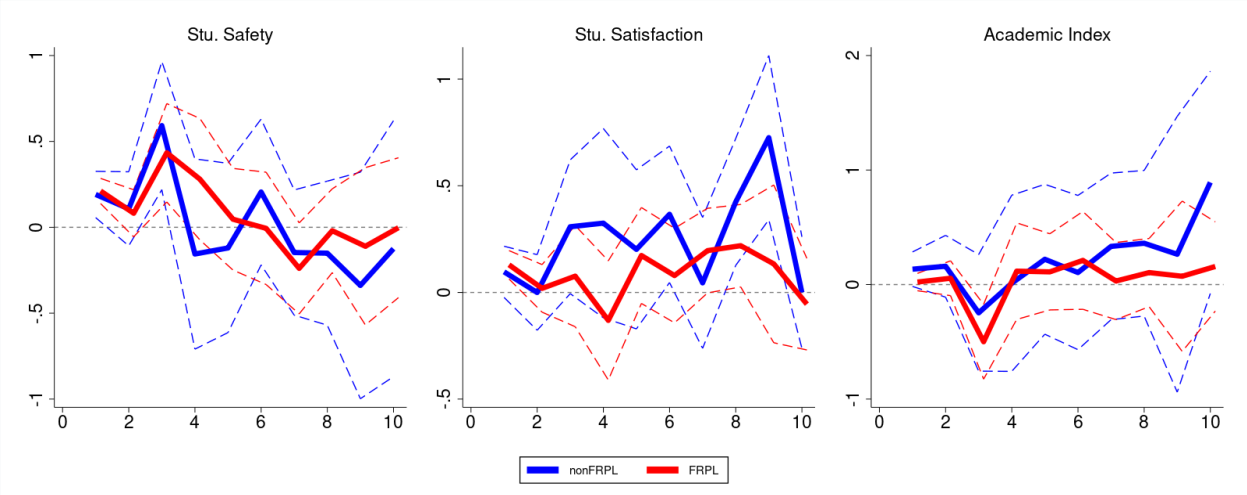
Notes: This figure displays distribution regression estimates, based on equation 1, across students' neighborhood income by deciles. Estimates are multiplied by 10 for ease of presentation. Standard errors are clustered at the school-by-year level.

Figure A9: Overall Information Impacts by Incoming Math Score Decile and Subsidized Lunch Status



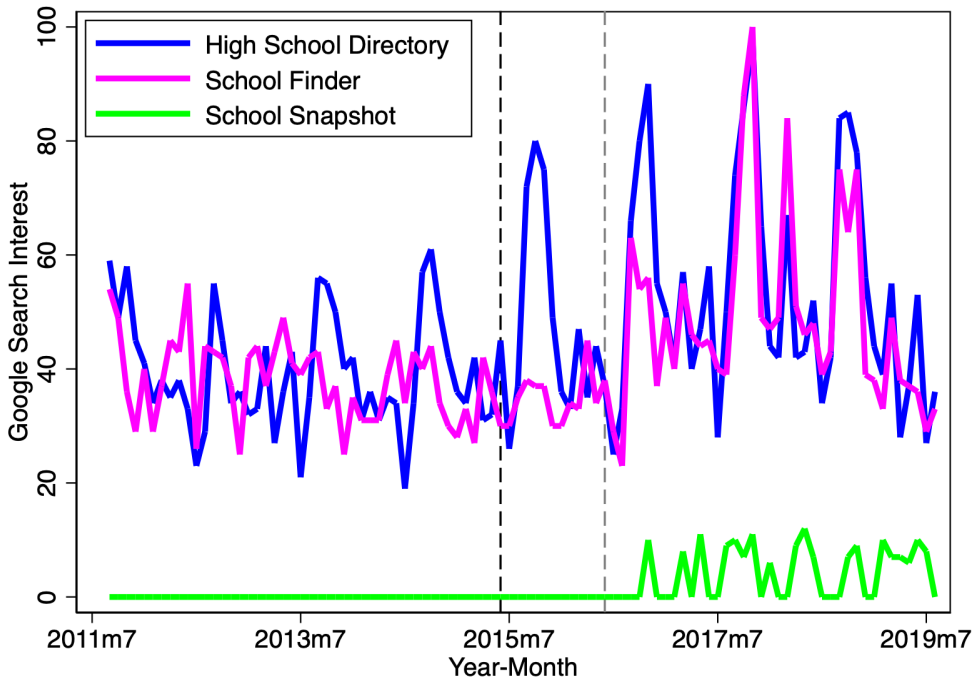
Notes: This figure displays distribution regression estimates, based on equation 1, across students' incoming 8th grade math achievement by deciles and subsidized lunch eligibility. Estimates are multiplied by 10 for ease of presentation. Standard errors are clustered at the school-by-year level.

Figure A10: Overall Information Impacts by Neighborhood Income Decile and Subsidized Lunch Status



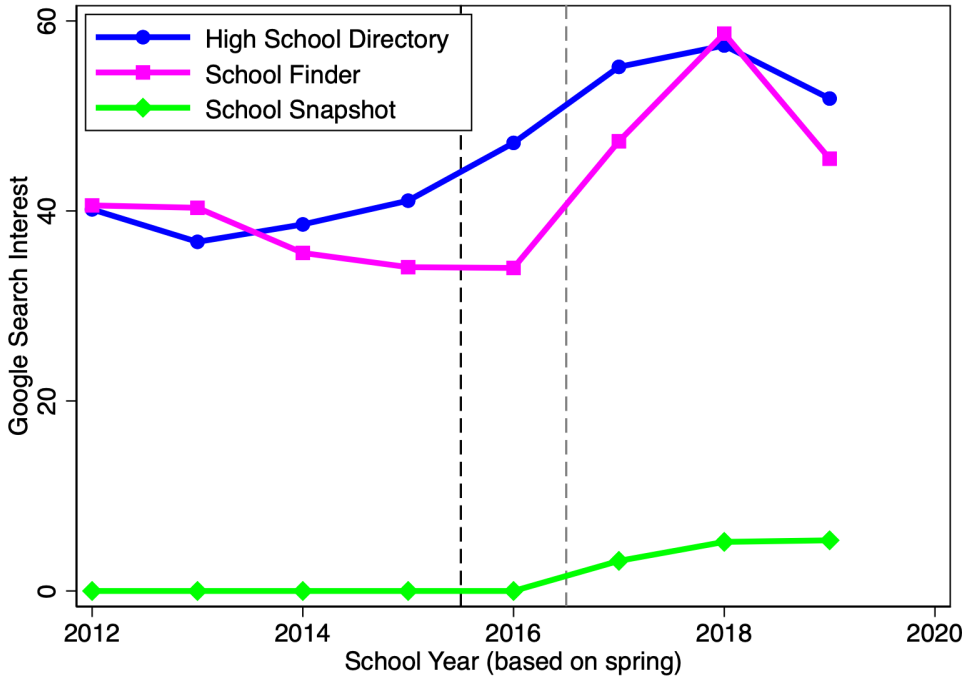
Notes: This figure displays distribution regression estimates, based on equation 1, across students' neighborhood income by deciles and subsidized lunch eligibility. Estimates are multiplied by 10 for ease of presentation. Standard errors are clustered at the school-by-year level.

Figure A11: Google Search Trends for Online School Information (Month-by-Year-level)



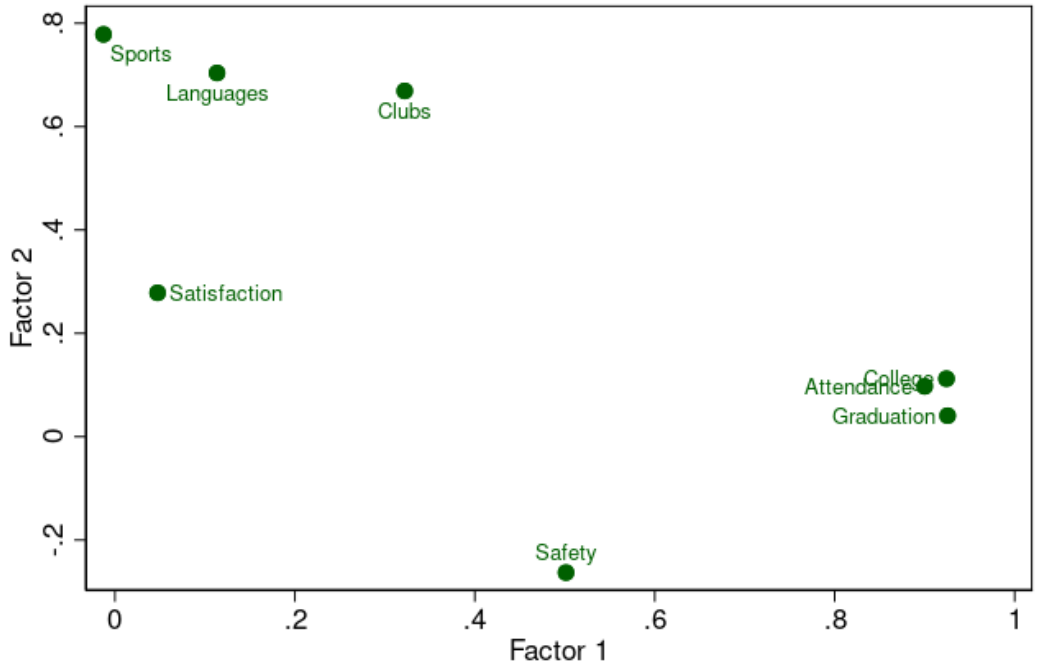
Notes: Google Trends search results for New York, NY between September 1, 2011 and August 31, 2019. The Google Trends website applied an improvement to data collection in on January 1, 2016, requiring cautious interpretation before/after that date. The black vertical dashed line separates the periods before/after the release of the student safety and satisfaction information. The gray vertical dashed line shows when the interactive online High School Directory was first released.

Figure A12: Google Search Trends for Online School Information (School-Year-level)



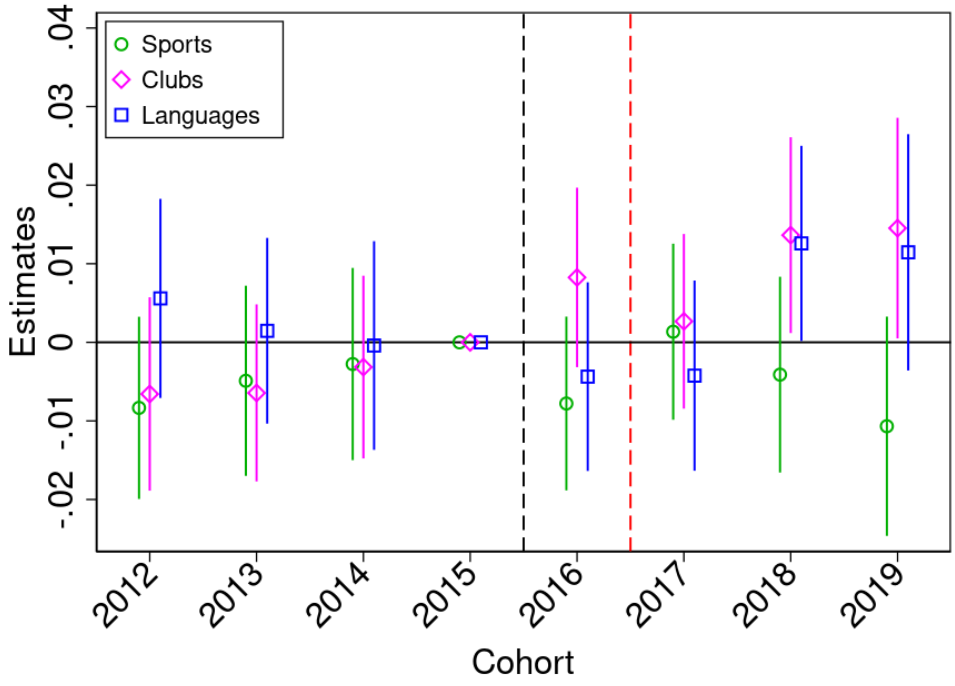
Notes: Google Trends search results for New York, NY between September 1, 2011 and August 31, 2019 (averaged by school-year, between each September through August). The Google Trends website applied an improvement to data collection in on January 1, 2016, requiring cautious interpretation before/after that date. The black vertical dashed line separates the periods before/after the release of the student safety and satisfaction information. The gray vertical dashed line shows when the interactive online High School Directory was first released.

Figure A13: Unrotated Factor Loadings Plot



Notes: The analysis uses actual data of eight school characteristics, based on years 2012 through 2015. Principal component analysis conducted using *factor* command in Stata with the pcf option, which is then followed by *rotate*, and lastly by *loadingplot*.

Figure A14: Impacts of Directory Extracurriculars Information Shocks on Families' Preference Percentile Rank



Notes: Event study is based on equation 2, where the only school information is based on the average number of extracurriculars between 2017 through 2019, in perentile terms. The black vertical dashed line separates the periods before/after the release of the students safety and satisfaction information. The red vertical dashed line shows when the interactive online High School Directory was first released.

Table A1: Weights Used to Compute Directory Information Indexes

Academic Index (Directory Info.: yearly updated)	Weight
Graduation Rate	0.363
College Enrollment Rate	0.363
Attendance Rate	0.354

Academic Index (Directory Info.: 16-17 avg)	Weight
Graduation Rate	0.345
College Enrollment Rate	0.355
Attendance Rate	0.355

Table A2: Associations between families' preference percentile rankings and school characteristics (pre-shock period between 2012 and 2015

Full Sample	By Incoming Math Score		By Subsidized Lunch		By Neighborhood Income		By Race/Ethnicity			
	Below Median	Above Median	Eligible	Ineligible	Below Median	Above Median	Asian	Black	Latino	White
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: Association between families' PPRs and school ***Student Safety*** *percentile*										
0.528	0.216	0.866	0.485	0.623	0.502	0.453	1.173	0.210	0.509	0.388
(0.008)	(0.012)	(0.012)	(0.009)	(0.016)	(0.009)	(0.018)	(0.022)	(0.014)	(0.012)	(0.028)
Panel B: Association between families' PPRs and school ***Student Satisfaction*** *percentile*										
0.756	0.572	0.947	0.692	0.933	0.562	1.283	1.363	0.382	0.647	1.336
(0.008)	(0.012)	(0.012)	(0.010)	(0.018)	(0.010)	(0.019)	(0.024)	(0.014)	(0.013)	(0.031)
Panel C: Association between families' PPRs and school ***Academic Index*** *percentile*										
1.263	0.919	1.957	1.188	1.527	1.084	1.874	2.867	1.019	1.016	1.637
(0.009)	(0.012)	(0.014)	(0.010)	(0.019)	(0.010)	(0.023)	(0.032)	(0.015)	(0.013)	(0.039)
1,302,171	672,175	629,996	999,625	302,546	1,035,211	266,960	175,491	454,458	558,545	113,677

Note: Estimates are multiplied by 10 for ease of presentation. The outcome of interest is families' preference percentile ranking of a school, while the independent variable is the percentile for each school characteristic (based on the average of the information between 2016 and 2017). Bottom row displays the number of observations for each column's subsample. Standard errors (in parentheses) are clustered at the student-by-year level.

Table A3: Information Impacts on Families' Preference Percentile Rankings (PPRs)

	(1)	(2)	(3)	(4)	(5)	(6)
Stu. Safety$_{2016–2017} \times (t \geq 2016)$	0.141***	0.133***	0.134***	0.140***	0.121***	0.144**
	(0.035)	(0.036)	(0.035)	(0.036)	(0.036)	(0.064)
	[26.7%]	[25.2%]	[25.4%]	[26.5%]	[22.9%]	[27.3%]
Stu. Satisfaction$_{2016–2017} \times (t \geq 2016)$	0.118***	0.120***	0.117***	0.121***	0.118***	0.101**
	(0.031)	(0.031)	(0.030)	(0.031)	(0.031)	(0.051)
	[15.6%]	[15.9%]	[15.5%]	[16.0%]	[15.6%]	[13.4%]
Academic Index$_{2016–2017} \times (t \geq 2016)$	0.055	0.047	0.046	0.056	0.012	0.074
	(0.035)	(0.035)	(0.035)	(0.036)	(0.035)	(0.065)
	[4.4%]	[3.7%]	[3.6%]	[4.4%]	[1.0%]	[5.9%]
Observations	2,408,462	2,408,462	2,408,462	2,408,462	2,408,462	2,408,462
Time-varying Safety, Satis., Acad. controls	✓		✓		✓	✓
ln(distance) control	✓			✓	✓	✓
Time-varying school demographics					✓	
Information-shock pre-trends						✓

Notes: Information impact estimates are multiplied by 10 for ease of presentation. Estimation is based on variations of equation 1, where the information shocks are based on the 2016 to 2017 average for each school characteristic. Percent impacts (in brackets) are calculated by dividing the DID estimate by the corresponding pre-shock period association. Standard errors are clustered at the school-by-year level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: Information Impacts on Families' Preference Percentile Rankings (PPRs), with yearly-updated information

	(1)	(2)
Stu. Safety$\times(t \geq 2016)$	0.141***	0.100**
	(0.035)	(0.040)
	[26.7%]	[11.4%]
Stu. Satisfaction$\times(t \geq 2016)$	0.118***	0.107***
	(0.031)	(0.035)
	[15.6%]	[11.5%]
Academic Index$\times(t \geq 2016)$	0.055	0.058
	(0.035)	(0.036)
	[4.4%]	[4.3%]
ln(distance)	-0.035***	-0.035***
	(0.001)	(0.001)
Observations	2,408,462	2,343,838
Year-to-year info changes		✓

Notes: Information impact estimates are multiplied by 10 for ease of presentation. Estimation is based on variations of equation 1. Column (1) presents the main model, where the information shocks are based on the 2016 to 2017 average for each school characteristic. In column (2), the shocks are based on yearly-updated directory information, and therefore, include main effects for each the three school characteristics as controls. Percent impacts (in brackets) are calculated by dividing the DID estimate by the corresponding pre-shock period association. Standard errors are clustered at the school-by-year level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: Information-shock effects on families' school choices at different ranking thresholds

	Top 3 (1)	Top 2 (2)	Top 1 (3)
Stu. Safety × (t≥ 2016)	0.231***	0.219***	0.104**
	(0.053)	(0.054)	(0.044)
	[73.6%]	[51.4%]	[25.4%]
Stu. Satisfaction × (t≥ 2016)	0.156***	0.165***	0.117***
	(0.048)	(0.050)	(0.039)
	[8.8%]	[10.2%]	[10.5%]
Academic Index × (t≥ 2016)	0.126**	0.036	-0.006
	(0.057)	(0.055)	(0.043)
	[6.9%]	[2.1%]	[-0.5%]
ln(distance)	-0.071***	-0.073***	-0.058***
	(0.002)	(0.002)	(0.002)
Observations	2,408,462	2,408,462	2,408,462

Estimates are multiplied by 10 for ease of presentation. Estimation is based on variations of equation 1. The outcomes in this table are indicators for whether or not the specific chosen school was ranked in the top 3, 2, or 1 choices. All specifications include demographic-cell-by-year and demographic-cell-by-school fixed effects; additional controls vary by column as indicated. Percent impacts (in brackets) are the DID estimate divided by the corresponding pre-period association. Standard errors (in parentheses) are clustered at the school-by-year level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix B Promotion and Use of SchoolFinder

Although the online directory–School Finder–was technically available in 2017, it may not have been a widely adopted source of high school information until 2018. Evidence for this mechanism emerges, first, from how the New York City Department of Education (NYCDOE) promoted School Finder. In the 2017 printed high school directory, NYCDOE did not highlight School Finder as a primary resource. Instead, the directory instructed students to "review the 2017 New York City High School Directory; make a list of schools that interest you" (p. iv). Similarly, NYCDOE tweets from May to August 2016 encouraged students to "Get #ReadyForHS with the 2017 NYC #HighSchool Directory" by downloading a PDF version of the paper directory.

Public promotion of School Finder began on September 12, 2016, when NYCDOE described it as a new tool to "help students, families and school counselors find HS choices for applications." However, this promotion occurred several months after the 2017 cohort likely began their high school search process, suggesting limited early adoption.

In contrast, NYCDOE consistently promoted School Finder as a primary resource for the 2018 cohort. The 2018 printed directory listed School Finder as the first recommended tool for exploring high school options, encouraging students to "explore 12 choices for your High School Application on your mobile or desktop device" and "find high schools based on your interests, location, and more." NYCDOE's Twitter account reinforced exploring School Finder as the first step in the high school application process for the 2018 cohort, promoting the website throughout summer and fall 2017. Thus, while the online directory was publicly available in fall 2016, due to public promotion its impact was likely muted for the 2017 cohort and more pronounced for the 2018 cohort.

Additional support for this mechanism comes from online search behavior. Google Search Trends data in Figure A12 tracks how New York City residents searched for high school directory-related terms from 2012 to 2019. The blue line represents searches for "High School Directory," the pink line represents searches for "School Finder" (the official name of the online directory), and the green line represents searches for "School Snapshot"(NYCDOE school quality reports). The dashed black line indicates when NYCDOE began publishing student safety and satisfaction information in the directory, while the dashed gray line marks the launch of the online directory.

Notably, in 2017, searches for "School Finder" increased following its launch but remained significantly lower than searches for "high school directory." By 2018, after NYCDOE more actively promoted School Finder, searches for "high school directory" and "school finder" converged. These trends further suggest that although School Finder was introduced in

2017, NYC families may not have widely adopted it as a key school choice resource until 2018. Once the online directory was a key resource, increasing the salience of information about schools' student satisfaction and academics and families access to this information on computers and smart phones, the relationship between these school characteristics and families' school rankings increased.[45]

[45]Figure A11 presents monthly Google Trends data results.