Beyond Test Scores: Does Public Information on School Satisfaction and Violence Levels Affect Parental School Choice?

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March 2025

Abstract

Amid the proliferation of school choice policies, substantial disparities persist in the quality of schools selected by high and low socioeconomic-status (SES) families. Can we decrease this gap by providing parents with better information, and if so, what information is effective at inducing parents to select better schools? To address these questions, I leverage a unique natural experiment in Israel, where a Supreme Court ruling mandated the public release of comprehensive school-level information. Employing a discrete choice model, an event study design, and a difference-in-difference approach, I examine the impact of this information disclosure on student school choice. I find that in regions with multiple school options, following the information disclosure, parents increasingly favor schools with better attributes. Notably, this shift is primarily attributed to factors such as violence levels and students' school satisfaction ratings, rather than test score information. Importantly, I find that the effect is driven by the increased response of lower SES households to the non-score-related attributes, narrowing the preexisting selection gap from their high SES counterparts. Crucially, I establish a robust association between school violence levels and school value-added measures, and find that lower SES households were more likely to select schools with higher value added following the information disclosure. Furthermore, I find that schools respond to the increased accountability by improving in the non academic publicized attributes. Finally, I identify information-sharing networks, based on shared ethnic and cultural ties, influencing school choices. My findings demonstrate the importance of providing a diverse set of school attribute information to enhance equity, academic outcomes and social mobility.

*geniar@tauex.tau.ac.il. I want to thank Jonathan Guryan, Victor Lavy and Joel Mokyr for their time, effort and thoughtful advice on this project. I thank Netanel Ben-Porath, Christopher Campos, Michael Dinerstein, Marie-Louise Décamps, David Figlio, Walker Hanlon, Ofer Malamud, Matthew Notowidigdo, Alesandro Pavan, Imran Rasul, Analia Schlosser, Silvia Vannutelli and attendees of Northwestern's various seminars, and APPAM, SEA and NBER conferences for helpful discussions and advice. Finally, I would like to thank the Israeli Education Ministry for providing access to their datasets. All errors are my own. Tables and figures are located at the end of the paper in the order they appear in the text, followed by the appendix. First version: October, 2023

1 Introduction

Each year, millions of parents around the world decide which school their child should attend. This choice has important consequences both on the child's future outcomes (Abdulkadiroğlu et al., 2018, 2020; Muralidharan and Sundararaman, 2015; Walberg, 2007; Campos and Kearns, 2022; Lavy, 2010, 2021) and on the funding and incentives schools and teachers receive (Hoxby, 2000; Figlio and Rouse, 2006; Angrist et al., 2002). With the large expansion in school choice policies in recent years, a crucial debate centers on their consequences for student and school improvements and on the implications to equity in opportunity and resources (Musset, 2012; Neilson, 2019).[1] Regardless of the specific choice mechanism, the extent to which households have access to accurate and comprehensive information about their choices is a key factor in ensuring that school choice leads to better and more equitable outcomes for students.

A commonly used solution by policy makers has been to make standardized test score information public. While previous research has shown that providing information on average student test scores and academic value-added (VA) measures can yield positive responses from households (Hastings and Weinstein, 2008; Ainsworth et al., 2023; Campos, 2023; Neilson et al., 2019), a large proportion of households remain unresponsive to this information, particularly among those from lower socioeconomic backgrounds. This lack of responsiveness carries significant adverse implications for equity (Hastings et al., 2010; Fuller and Elmore, 1996). A growing body of work emphasizes the multidimensional nature of the education production function (Beuermann et al., 2023). This gives rise to the possibility that families may prioritize different dimensions which have a stronger impact on their children. Lower socio economic status (SES) families may prioritize school safety and a supportive atmosphere rather than simply focusing on test scores. This hypothesis would highlight the need for a more holistic approach to information disclosure, where a diverse set of attributes related to the school environment is included in the information set.[2]

In this paper, I study an Israeli Supreme Court information disclosure mandate, where the Ministry of Education was ordered to release academic and non-academic school-level information, including test scores, student satisfaction ratings and levels of school violence. This information was subsequently featured on mainstream digital media and major apartment

[1] School choice policies encompass a range of options, including public school choice linked to open enrolment policies, access to private school alternatives, either through private funding or government-funded initiatives such as vouchers and savings account deposits, as well as enrollment in specialized schools like vocational, charter, or magnet schools. These policies have been widely adopted, with nearly all states in the US and OECD countries implementing some form of school choice. According to an OECD report, approximately 77 percent of students, on average across OECD nations, and 76 percent in the US, have the opportunity to choose from two or more schools for their children, based on school principal surveys (OECD, 2019).

[2] For a discussion on the potential contribution of an array of schools attributes to its quality, see Hanushek (1971); Kautz et al. (2014); Jackson (2018), and Lavy et al. (2023).

seeking websites. The richness of the disclosed information allows me to assess how families responded to the multidimensional nature of school choice and examine SES heterogeneity in priors and parental response. It further allows me to test which school attributes are linked with VA measures and explore the subsequent implications of information disclosure for selection into higher quality schools as well as for mobility and social integration.

To examine the effects of information on school choice, I investigate the choices made by students transitioning from 6th to 7th grade in municipalities where parents had the option to choose from several middle school options.[3] Using a discrete choice model, which looks at within student decisions, I estimate the utility weights parents place on each school attribute when making their school choice. I then employ an event study design to estimate whether parents placed larger weights on the different school attributes in the years following the release of information. An increase in the weights assigned to a specific attribute among parents of cohorts transitioning to middle school after the information release suggests that parents responded to the newly available information about that attribute. This indicates both their interest for this attribute and the absence of sufficient prior implicit or explicit information related to it. Furthermore, I explore difference-in-difference estimates to examine differential response in choice sets with larger disparities in school attributes between the different school options, versus choice sets with smaller differences.

In addition to the unique extensive simultaneous disclosure of information on a range of school attributes, our setting possesses several advantageous features to explore parental responses to school information. First, the exogenous intervention by the Supreme Court, which did not align with any plans by the Education Ministry or the schools, provides an ideal natural experiment. This allows me to test the effects of information disclosure without the influence of specific goals by the education body in charge or accompanying policy changes which might threaten the identification, as is potentially the case in other settings for which school information disclosure was examined. Second, the information was picked up and highlighted by major digital news outlets rather than actively disseminated to parents. This feature, while still providing sufficient salience to reach parents, offers a more natural method of information spread compared to the strong targeted interventions in most previous studies (Hastings and Weinstein, 2008; Neilson et al., 2019; Ainsworth et al., 2023). Additionally, prior to the information release, there was no available official public school level information. This allows me to examine the effects at the earliest stage of information disclosure.

The Israeli schooling system resembles the structure, curricular focus and government investment of most developed economies. It is almost solely public and does not permit screening students upon entry to primary or middle school, with very few exceptions. Ca-

[3] Or systematically influence their child's school assignment through appeals or address manipulation on registration forms.

pacity constraints are generally not binding in this context. For the few schools that receive more applicants than their capacity allows, a lottery system is implemented. These characteristics reduce the risks of selective attrition and enable an analysis of the decisions and shifts in the choices made by the entire population of school-goers, encompassing the entire SES distribution. This setting offers a unique opportunity to accurately estimate the response to information by isolating the effect of the information on parental demand from school strategic supply side considerations. Additionally, the availability of administrative information on parental schooling levels, combined with the fact that information disclosure was equally accessible across the SES distribution, facilitates an investigation of heterogeneous responses by SES. This also allows for an estimation of the effects of the intervention on socio-economic integration. Moreover, the extensive administrative data includes rich demographic data, high school and middle school test scores and matriculation levels, and lagged individual test scores in 2nd and 5th grade. This allows me to credibly estimate VA measures and incorporate them into the analysis. The data also includes information on gender, ethnicity and immigrant status, allowing further exploration into the heterogeneity of response.

This setup yields six main findings, which I use to organize the exposition and frame the paper's contribution. They are as follows.

1. Parents respond to the information disclosure by selection into schools with higher satisfaction ratings and lower violence levels, and to a lesser extent, to test scores.

Compared to the years prior to the information release, on average, I estimate an increased probability of 1 percentage point of attending schools with a 1 SD lower violence level and 3 percentage points with a 1 SD higher satisfaction rating. The effect relating to average test score information, is similar, with an increased probability of 2 percentage points. The results indicate stronger responses when choice sets exhibit larger differences in satisfaction and violence ratings. In choice sets where the rating differences between the 'best' and 'worst' options are above the median for the relevant attribute, I estimate an increased probability of 3 percentage point for attending schools with a 1 SD lower violence level and 11 percentage points with a 1 SD higher satisfaction rating. This suggests that greater disparities create stronger incentives for parents to respond to information regarding these attributes. I do not find a similar pattern for test scores. These results relate to the literature on parental response to school quality information (Ainsworth et al., 2023; Hastings and Weinstein, 2008; Neilson et al., 2019). The contribution of this paper is to emphasize the importance to parents of non-score-related school attributes (Facchetti et al., 2024; Beuermann et al., 2023) and highlight the importance of the previously unexplored information disclosure of alternative aspects of school atmosphere such as satisfaction and violence levels.

2. Response to information is concentrated among lower SES households and among native born students. Households of male students also exhibit a stronger response to violence information.

Response to information concerning satisfaction and violence ratings was significantly larger for lower SES households, particularly in the subset with above-median choice set differences. In this subgroup, there was a differential increase in the probability of 10 and 6 percentage points for lower SES households compared to their high SES counterparts. Conversely, the response to information related to test scores was similar for both SES groups. These findings relate to the literature which explores the heterogeneity in school choice preferences and information acquisition associated with SES differences (Hastings et al., 2010; Beuermann et al., 2023; Hoxby and Avery, 2012; Schneider and Buckley, 2002). My contribution is presenting new supporting evidence for the idea that different socio-economic groups might possess and value different school attribute information and thus respond deferentially to information disclosure policies. While the literature suggests that higher SES households place more emphasis on test scores and lower SES parents may be more constrained by higher search costs and specific school-student matched attributes, and thus less responsive to school quality information (Hastings et al., 2010; Cohodes et al., 2022; DeLuca and Rosenblatt, 2010; Fuller and Elmore, 1996; Mani et al., 2013). This finding brings new insights, by offering novel evidence on tangible, quantifiable school indicators that lower SES families seem to value more than test scores, such as school satisfaction and violence levels. This suggests lower SES households are not necessarily over constrained by specific student school matched attributes such as geographical proximity or student composition factors. Instead, they might value different school attributes compared to their higher SES counterparts.

I further find that the lack or response among higher SES parents was, in part, due to their pre-existing sorting into schools with superior test scores, lower violence levels, and higher student satisfaction ratings within their choice sets, even before the information disclosure. This finding suggests that higher SES households were able to gather accurate information even prior to the release of public information. In contrast, lower SES households did not exhibit a similar pattern of positive selection before the disclosure, implying that they were less likely to access accurate and credible information without publicly available data. This finding relates to the literature on SES differences in information acquisition (Hoxby and Avery, 2012; Schneider and Buckley, 2002; DeLuca and Rosenblatt, 2010; Ben-Porath, 2009). It contributes to this literature by providing evidence relating to the disparities in scenarios with no publicly available information, in settings with large differences within the choice set, and for various attributes beyond test scores, including those that lower SES households

appear to value. Furthermore, the findings underscore the potential for even non-targeted publicly released information to enhance equity in school quality information.

While some research has identified gender differences in the way children respond to school quality and peer characteristics (Lavy et al., 2012b; Jacob, 2002), previous studies related to information disclosure did not find gender related differential response to information on test score (Hastings and Weinstein, 2008) or VA measures (Ainsworth et al., 2023). I contribute to this literature by presenting novel evidence that households of male students exhibit a stronger response to information related to violence levels, with an average increased probability of 2 percentage points. Additionally, I find novel evidence of potential information frictions for immigrant households, emphasizing the need for specific interventions to ensure equitable access to information (Corcoran et al., 2018).

The findings related to both SES and gender heterogeneity are consistent with the idea that the response to information might depend on the perceived sensitivity of the student to the school attribute. Lower SES students may be more influenced by alternative school attributes, such as violence and socio-emotional factors (Jackson et al., 2023; Cunha et al., 2010; Lavy et al., 2012a), while male students may be particularly affected by the level of violence (Lavy and Schlosser, 2011). I incorporate this perceived sensitivity as part of the random utility model of school choice.

3. Violence ratings are strongly connected to school VA measures, while there does not appear to be a significant connection between VA and satisfaction levels or test scores.

As parents select into schools according to different attributes, it is important to estimate the link between those school attributes and school VA measures. I estimated VA for each middle school based on its effect on end of high school student average matriculation scores, controlling for lagged test scores during primary school and a range of different demographic characteristics.[4] I find that violence levels were strongly correlated with VA measures (correlation = 0.29). In contrast, satisfaction levels and middle school test scores were not strong indicators of school quality, with a correlation of -0.1 and -0.08, respectively, with the VA measures. Interestingly, when calculating VA measures without controlling for primary school test scores, the correlation with violence levels remained consistent, while the correlations with satisfaction levels and middle school test scores would have appeared strong and positive (0.23, 0.52, and 0.62, respectively).

[4]I used end of high school outcomes as my main VA specification for several reasons. First, part of the added value of middle schools is to allow a student to get accepted into a better high school and prepare the student for high school studies. Second, in our setting, data on middle school tests is only available for some students and is administered midway middle school in a low stakes environment, indicating a lower reliability of such tests compared to end of high school exit exams. Conclusions are robust to the use of high school graduation rates as an alternative measure to average test scores on the exit exams.

These findings align with the literature that questions the robustness of the connection between standardized test scores and school VA measures (Fabregas, 2023; Campos, 2023). They also resonate with research emphasizing the importance of considering multidimensional aspects when determining school quality (Beuermann et al., 2023; Riehl et al., 2018). The novelty of this findings lies in highlighting the crucial role of school violence levels in determining school quality. Additionally, it sheds light on the potential disconnect between VA measures and commonly publicized test scores, a widely used measure. It is important to note that while satisfaction levels may not exhibit a strong connection with VA measures based on test score success, it shouldn't necessarily diminish the attribute's value. The well-being of children in school is a valuable goal for both parents and schools and can have significant long-term effects beyond high school success (Jackson et al., 2020, 2023).

4. The information disclosure led to positive selection into better quality schools, especially for students from lower SES households.

Following the information disclosure, I observe increased selecting into schools with higher VA for choice sets with larger disparities in school violence levels. This finding aligns with the idea that parents chose schools with lower violence levels post disclosure. Given the positive correlation between violence levels and school VA, this choice led parents to opt for higher-quality schools. Furthermore, I observed that the positive selection into schools with higher VA following the information disclosure was more pronounced among students from lower SES households, consistent with their stronger response to information about school violence levels. Additionally, I find no evidence of an increase in the levels of social segregation between schools following the information disclosure.

These findings relate to the literature which examines the connection between information provision and more beneficial academic choices (Jensen, 2010; Cohodes et al., 2022; Haaland et al., 2023; Ainsworth et al., 2023; Hastings and Weinstein, 2008). The main contribution of this finding is providing novel supportive evidence for the potential of information disclosure which includes non test score related attributes to positively influence selection into schools with higher VA. As well as providing evidence that disclosing non test score related school level information may encourage lower SES families to choose higher quality schools, potentially benefiting social mobility.

5. Information disclosure drives schools in regions with school choice to improve their measured school attributes.

Previous literature finds that school competition stemming from school choice can lead

to improved school quality (Campos and Kearns, 2022; Hoxby, 2000, 2003; Figlio and Rouse, 2006). However, the role of information in driving these accountability incentives—and whether accountability for non-academic attributes leads schools to improve on those outcomes, along with the trade-offs involved—remains less clear. Utilizing the unique setting, I find that following the information disclosure and after an adaptation period, schools in regions with school choice differentially improved their students' satisfaction and violence ratings, without significant changes in test score ratings. Results remain unchanged after accounting for changes in the characteristics of attending students, suggesting that these improvements can be attributed to school response rather than to compositional changes driven by household choice.

Using an unconditional quantile regression analysis, I further find that the improvements were generally evenly spread out across the rating distribution, with schools exhibiting higher initial violence levels experiencing slightly larger improvements. Finally, I find that high value-added schools in regions with school choice experienced a differential decrease following the information disclosure, suggesting that school strategies driven by accountability on the measured attributes may partly come at the expense of student academic improvement.

6. School attribute information seems to be shared through networks of informal relationships in the classroom based on similar ethnic background

Immigrant households with a common origin, who share the same primary school class, are more likely to choose the same middle school option following the information disclosure. This increased concentration, which I estimate using the Herfindahl–Hirschman index (HHI), is associated with a higher likelihood of attending the highest-ranked middle school option in terms of student satisfaction ratings. This effect is not present for the entire primary school class, providing supportive evidence for the existence of information sharing networks among households which are likely to form relationships based on cultural similarities and a shared foreign language. These informal networks increase the probability that their members will choose schools based on the disclosed information. This idea is further supported by evidence showing that the number of intragroup peers in the classroom positively affects the probability of responding to school attribute information.

These findings relate to the literature on the role of social interactions in information dissemination (Banerjee et al., 2021; Golub and Sadler, 2017). In related settings of school choice, Facchetti et al. (2024) and Campos (2023) document the existence of information spillovers relating to school VA measures and general parents information sharing sessions. I contribute to this literature by identifying the existence of specific informal information groups and the basis for their formation. I also provide evidence for the potential existence of information

sharing in a context where the information is public and available to all participants. Additionally, I identify a mechanism of information dissemination related to non-academic school quality attributes.

The rest of the paper is organized in the following way. Section 2 provides the institutional background of our setting. Section 3 presents the data and variable construction. Section 4 introduces the model and discusses the estimation strategy. Section 5 presents the results for each of our main findings related to household response and includes related discussions. 6 discusses how schools respond to the information disclosure. In Section 7 I discuss additional outcomes related to information networks and other aspects of school life. Section 8 concludes.

2 Institutional Background

2.1 The Israeli Education System

In Israel, the education system comprises several sectors, including Jewish secular, Arab, Jewish religious, and Ultra-Orthodox. Our analysis focuses on the first two sectors, where schools are primarily public, government-funded and follow a similar curriculum to most OECD countries. In most municipalities there are three levels of schooling. Primary school which children attend between 1st and 6th grade. Middle schools which children attend between grades 7 and 9 (and covers ages 12 to 15) and high school which runs from 10th to 12th grade. This three-tier model is similar to many countries including the US and parts of Europe.[5] Our primary focus in this paper is on middle schools, also known in other countries as intermediate school, junior high school, junior secondary school, or lower secondary school. The purpose of middle schools is to serve as a transition/preparatory period between the early education years of primary school and the more rigorous education years of the latter years.

In Israel, the assignment of students to middle schools can be organized through several methods, with each municipality having the autonomy to choose the appropriate method for different regions within its jurisdiction. The most common method involves each primary school having an assigned middle school, and it doesn't provide parents with any school choice options. Alternatively, some regions offer a choice set of several middle school options in close proximity, allowing parents to choose from several middle school options. A third approach permits parents to choose any middle school within the municipality.[6] For all the methods,

[5] In other countries the prevalent system is the two-tier model where students attend primary school commonly for the first 6 years of their compulsory education and then transition to secondary school/high school for the rest.

[6] Capacity constraints do not play a major role in this setting for several reasons. First, over registration to a school is not common as only around 10 percent of schools are at full capacity in the relevant years. Furthermore, capacity constraints do not seem to be correlated with higher ranked schools in the different

entrance exams or interviews to select students are prohibited. For our analysis, I focus on the latter two methods, which represent nearly 10 percent of all middle schools in the country.

The Education Ministry administers the Growth and Effectiveness Measures for Schools (GEMS - Meizav in Hebrew) testing to monitor effective teaching and school atmosphere for both primary and middle schools. The GEMS includes a series of tests and questionnaires administered by the Division of Evaluation and Measurement of the Ministry of Education. GEMS testing typically takes place towards the end of each school year, from mid-May to mid-June. It follows a representative 1-in-2 sample strategy, with every elementary and middle school in Israel participating in GEMS once every two years.[7] The GEMS dataset includes test scores for students in the second and fifth grades (primary school) and eighth grade (middle school) in subjects such as math, science, language, and English (second-grade tests include only math and language). These test scores are standardized for comparability across different years. Virtually all students, with the exception of those in special education classes, are tested, resulting in a testing rate exceeding 90 percent. In addition to the standardized tests, the GEMS program administers anonymous student questionnaires, covering a wide range of aspects related to the school and its learning environment.

In high school, to graduate, students need to pass the matriculation exams (*Bagrut* in Hebrew). To be awarded a matriculation certificate, students are required to pass exams in seven mandatory subjects and two or more elective subjects. When a student passes an exam, she is awarded credit units that increase with the exam's proficiency level. In particular, 21 credit units grant a student a certificate. This matriculation system is a high stakes environment as the certificate is a pre-requisite for studying at universities and most academic and teachers' colleges and test scores are used by universities and colleges as a selection device and can determine both the quality of the school and the major a student can be accepted to. Many countries administer a similar setup of end of high school exams like the *A-levels* in the UK, *Baccalauréat* in France and the *Matura* in many other European countries. In the US, this system is equivalent to a combination of receiving a high school diploma and passing the exit exams which many states administer.

Finally, the Israeli setting I examine is comparable to most of the developed world both in terms of the standardized testing system, and in terms of the curriculum taught in schools. The average class size is approximately 26 students and the ratio of number of students to teacher is approximately 15, which aligns with the OECD average of 21 students and 15 teachers per ratio, respectively (OECD, 2014). The average number of years of schooling is

attributes either pre or post disclosure, with a maximum correlation of 0.04 and 0.07, respectively. In the few instances of over registration, assignment is decided by a lottery with priorities based first on geographical proximity and the presence of older siblings already attending the school. These procedures did not change during the sample period, and could only serve to attenuate the effect.

[7] Beginning in 2015, GEMS testing was conducted once every three years for each school.

close to 13, similar to the US and UK figures (Johansson et al., 2013). Furthermore, the national expenditure on education relative to GDP is just above 7 percent, roughly in line with the OECD and the US averages (OECD, 2014).

2.2 The School Level Information Disclosure

In September of 2012, following a motion by the Movement for Freedom of Information, the Israeli Supreme Court ordered the Ministry of Education to make the GEMS information, including all test scores and survey information, public by school level for all past and future years.[8] Prior to the court ruling, the Ministry used the information for internal evaluations and only publicly released information aggregated at the municipality level, making any comparisons related to the choice set of middle schools based on this information impossible.

This court case and information release garnered extensive media coverage. In November 2012, '*Ynet*', one of Israel's most popular digital news outlets, collaborated with '*Madlan*', a well-known apartment-seeking website, to launch a project called '*The Israeli Education Map*'. This project mapped out all schools in Israel and allowed users to compare schools in the same region or city based on various features of the GEMS data. These features included test scores and three measures derived from student surveys, serving as proxies for student satisfaction, school violence levels, and teacher fatigue. Specifically, the first measure gauged the percentage of students who reported being happy in school, the second measured the percentage of students who reported being kicked or punched at school within the last month, and the third measured the percentage of teachers who reported feeling 'burned out'.[9] Appendix Figure A1 presents a translated illustration of how the *'The Israeli Education Map'* presented the information for the schools in each municipality to parents.[10] Additionally, information for each school, including all GEMS survey questions, was accessible on the Education Ministry's website, albeit in a less user-friendly format, requiring parents to search for each school and examine official detailed reports. Figure 1 outlines the timeline related to the court ruling, information publication and relevant school registration and start dates.

[8] The Ministry opposed this release for various reasons, primarily concerning concerns of potentially 'unfair' league table comparisons based solely on test scores, as well as fears that schools might overly prioritize test scores, leading to inefficient allocation of teaching time and potential incentives for score manipulation behavior.

[9] Notably, the information related to teacher fatigue did not elicit any significant response from parents in any of the specifications. Consequently, I will not discuss results related to it further in the paper, except as suggestive evidence that the entire effect of the information disclosure cannot be solely explained by the increased saliency of the publicized measures.

[10] Polling information in the US has found that 51 percent of parents report utilizing websites that rate and compare schools, suggesting the possibility of potentially high exposure to the '*The Israeli Education Map*' project (Tompson et al., 2013).

3 Data and Variable Construction

Test scores and survey data from the GEMS are linked to student administrative records collected by the Ministry of Education. The administrative records include the student's school and class assignment and student demographics, which I use to construct all students' background characteristics. Using the linked datasets, I create a repeated cross section of students and their choice sets of middle school options, along with those schools' attributes for the years 2010-2015. The sample is restricted to Jewish secular and Arab public schools that follow the same national curriculum and participate in the GEMS national testing. I exclude the religious and ultra-orthodox Jewish population from our analysis as they have different institutional settings. Furthermore, I limit the sample to primary schools and students which had more than 1 middle school option in their choice set, constituting approximately 10 percent of all schools. Our final sample includes 84,987 students, 204 elementary schools, 179 middle schools in 82 municipalities. Descriptive statistics about our data are presented in Table 1. As can be seen from columns (1) and (2) of the table, the choice sample is representative of the entire population of students as there are no significant differences between the two groups.

3.1 Defining the Choice Set

For each year between 2010 and 2015, I observe students who are transitioning from primary school to middle school (between 6th and 7th grade). For each student, I define the choice set as the set of all of the potential middle schools the child could choose to attend.[11] For each middle school, for all the years, I assign attributes from the last available pre-disclosure year to mitigate endogeneity concerns associated with the treatment. This approach more accurately replicates the information presented to parents in the press, which did not receive

[11] I define the choice set in the following way: 1. For each primary school i for each year t, I observe for each transitioning student, to which middle school j they are going to attend. 2. Then for each Primary school i, I define the choice set J_{it} as the set of all the middle schools to which students from primary school i transitioned in year t. 3. Since we are looking at a public school system, tuition is similar across all middle school options and student screening is not allowed, I define the choice set for each student who attended primary school i as all the js belonging to J_{it}. Several additional considerations are pertinent to the definition of choice sets. First, I limit our analysis to students in primary school where the size of J_{it} is at least 2, focusing on students with more than one middle school option. I further limit the sample to primary schools which had a constant number of middle school options throughout the entire period of the sample (i.e., the size of J_{it} was constant for $\forall t \in [2010, 2015]$). This approach enables comparisons of similar choices over the years and reduces the potential bias due to policy changes in school choice zones. Finally, as I lack comprehensive institutional information for all municipalities over the entire sample period, it is possible that in some primary schools in the sample, where the size of J_{it} is at least 2, students are directly assigned to several middle school options by the municipality, without school choice by the parents. However, since there were no consistent policy changes in assignment during these years, this potential issue could only bias our results downwards. In such regions, parental choice may be expressed by appealing the assignment decision and requesting a transfer, changing residence, or manipulating residential addresses in the registration forms. These behaviors demonstrate even stronger preferences for desired schools and are considered part of the effect.

annual updates. Specifically, for each middle school, I assign school average ratings for different attributes derived from the student survey (e.g., violence and satisfaction levels) and the average overall test scores from the latest year when the school underwent the GEMS assessment, with 2012 being the latest year available. Similar to the online information, I define violence and satisfaction ratings by the percentage of students who chose the 2 highest rating levels (4 or 5) on the violence and satisfaction questions. Results are robust to using a simple school average rating. I further categorize each choice set by calculating the range from the best to the worst option in each of the main attributes (overall test scores, satisfaction levels, and violence levels). Subsequently, I classify each choice set as either above or below the median of the ranges for all choice sets concerning each of those attribute. This categorization allows to potentially proxy for incentives to respond to the information reveal, as higher ranges indicate larger disparities for the attributes, which are now available to parents.[12] As can be seen from columns (3) and (4) of Table 1, the composition of students seems to be similar for choice sets with above and below median ranges.

3.2 Value Added Measures

In order to evaluate the VA for each middle school I estimate a conventional VA model based on school and student observable characteristics (Rothstein, 2010; Angrist et al., 2017). I estimate an education production function which includes standard school and student-level inputs and a middle school fixed effect, which captures school quality, and serves as our measure of school VA.

$$Y_{ijt} = \alpha_j + \beta X_i + \gamma Z_{jt} + \lambda \text{LA}_i + u_{ijt} \tag{1}$$

where Y_{js} is the end-of-high-school student average matriculation score for student i who attended middle school j is year t. For robustness, I also consider alternative measures of educational outcomes, including whether a student obtained a high school diploma and the average scores in the middle school 8th grade exams from the GEMS. α_j denotes the middle school fixed effect, which is our measure of interest for the VA estimation. The student controls (the X_{jt} vector) encompass variables such as gender indicators, the number of siblings, an immigrant status indicator, parental education levels, and six indicators of the student's ethnicity. Z_{jt} corresponds to school-level controls, including the number of classes, the number of students, and a measure of the decile representing the average economic status

[12] On the other hand, it is possible that higher disparities in school attributes could have made these differences more noticeable to parents who were already more involved in their children's education even before the information was released. As discussed later in the paper, this might have reduced the scope for significant changes in school choice among these households following the information release.

of the school's student composition, compiled by the Ministry of Education. LA_i refers to the average scores from the primary school's GEMS exams for student i, and serves as an ability control prior to transitioning to middle school. u_{ijt} is a normally distributed mean zero residual.[13] To account for the potential bias generated by using the estimated VA measures in subsequent analysis, I implement a robustness test using a Bayes shrinkage estimation strategy and construct an unbiased measure of school VA that accounts for noise in the measurement. Additional details on this robustness are provided in the section dedicated to discussing the VA results.

4 Modeling and Estimating School Choice

In order to estimate preferences for different school attributes and how those change following the school information disclosure, I combine a discrete choice model estimation with an event study analysis. For each year of our sample, I estimate the parameters of a random utility model, akin to Hastings et al. (2010), in which parents choose the middle school that maximises their utility. This utility is represented as a linearly separable function of the predicted effect for their child of the different school's attributes. That is,

$$U_{ij} = \lambda^{A}_{g(i)} A^{p}_{ij} + \lambda^{V}_{g(i)} V^{p}_{ij} + \lambda^{S}_{g(i)} S^{p}_{ij} + \epsilon_{ij} \tag{2}$$

Where A^{p}_{ij}, V^{p}_{ij} and S^{p}_{ij} represent the predicted effect of school j's test scores, violence levels and satisfaction ratings on child i, respectively. While $\lambda^{A}_{g(i)}$, $\lambda^{V}_{g(i)}$,$\lambda^{S}_{g(i)}$ are the weights households place on each of these effects, respectively. The weight households place on each of the attributes can also vary with observable student characteristics g such as SES, gender, etc., and may depend on the value they place on the effect of the attribute on their child. Importantly, the weights can also depend on the information, or lack there of, that households posses relating to each attribute, which might cause them to place less expressed weight on that attribute. ϵ_{ij} represents all other idiosyncratic factors effecting the utility from the match.

As I do not observe the predicted effect of the different attributes at each school directly, I assume that their effects on student i at school j are proportional to a latent measure of the attribute at each school. For each of the attributes, This latent measure is the sum of the school average ratings (A_j, V_j and S_j), and an idiosyncratic match between the school and

[13] I treat the estimated VA as a reliable approximation of the true casual effect of schools on test scores. Previous studies indicate that VA models controlling for a comprehensive set of students' demographic characteristics and previous scores (as is done in this case), provide a good, albeit slightly biased, representation of the true causal effects estimated through random assignment (Angrist et al., 2017; Deming, 2014).

the student for each of those attributes (γ_{ij}, δ_{ij} and ω_{ij}).

$$A_{ij}^{p} = \kappa_{g(i)}^{A} A_j + \gamma_{ij} \tag{3}$$

$$V_{ij}^{p} = \kappa_{g(i)}^{V} V_j + \delta_{ij} \tag{4}$$

$$S_{ij}^{p} = \kappa_{g(i)}^{S} S_j + \omega_{ij} \tag{5}$$

The parameter κ captures sensitivity of students to the effect of each of the school attributes, where κ may also vary with g. Students with higher κ are more effected from attending a school with a higher level of that attribute.

Given these assumptions, we can rewrite our utility function in terms of observable school attributes as:

$$U_{ij} = \beta_{g(i)}^{A} A_{ij} + \beta_{g(i)}^{V} V_{ij} + \beta_{g(i)}^{S} S_{ij} + \zeta_{ij} \tag{6}$$

Where $\beta_{g(i)}^{A} = \lambda_{g(i)}^{A} \kappa_{g(i)}^{A}$, $\beta_{g(i)}^{A} = \lambda_{g(i)}^{A} \kappa_{g(i)}^{A}$, $\beta_{g(i)}^{A} = \lambda_{g(i)}^{A} \kappa_{g(i)}^{A}$ and $\zeta_{ij} = \lambda_{g(i)}^{A} \gamma_{ij} + \lambda_{g(i)}^{V} \delta_{ij} + \lambda_{g(i)}^{S} \omega_{ij} + \epsilon_{ij}$. Equation (6) determines parents choice of middle school based on a combination of observable school characteristics and the idiosyncratic weights that parents place on these and other unobserved characteristics.

Next, I estimate the coefficients from equation (6) for every year in our sample and determine whether there are significant shifts in the coefficients in the years following the information reveal. Such shifts in a coefficient of an attribute would indicate that parents received new information and value the information they received for that attribute.[14] I use an event study design in order to estimate whether there were significant shifts in weights parents assign to the different school attributes,

[14] A potential alternative explanation would be that the attribute has become more salient due to the information publication. In a later section I discuss why saliency is unlikely to explain the entire effect. In any case, the increased saliency can be considered as part of the effect of the information reveal. Alternative explanations related to changes in unobserved characteristics such as the sensitivity of students to certain attributes (κ), distance to the school, student composition and other explanations not related to the information disclosure are unlikely as there were no other interventions or institutional changes during the transition between the before and after years. And because other, less publicized, measures do not exhibit a similar effect, as I will discuss in a later section.

$$U_{ij} = \sum_{t=2010}^{2015} (\beta_t^A A_{ij} \times \mathbf{1}\{i \in \Gamma_t\} + \beta_t^V V_{ij} \times \mathbf{1}\{i \in \Gamma_t\} + \beta_t^S S_{ij} \times \mathbf{1}\{i \in \Gamma_t\}) + \zeta_{ij} \quad (7)$$

Where $\mathbf{1}\{i \in \Gamma_t\}$ is a cohort indicator $t \in \{2010, 2011, 2012, 2013, 2014, 2015\}$, with 2012, the last pre treatment year for the risers to middle school in our sample, omitted and serving as the baseline year.

I estimate the parameters of equation (7) using the conditional logit model.[15] The likelihood function is formed by maximizing the probability that student i chooses to attend middle school j over the other options in her choice set:

$$P_i(j_i) = Pr(U_{ij} > U_{ik} \forall k \in J_i) = \frac{\exp(\beta^A A_j + \beta^V V_j + \beta^S S_j)}{\sum_{k \in J_i} \exp(\beta^A A_k + \beta^V V_k + \beta^S S_k)} \quad (8)$$

Where J_i is the choice set of middle school options for student i. A_j,V_j and S_j are, standard normal attributes for middle school j from the most recent pre treatment GEMS survey, representing the school average GEMS test score in 8th grade, the percentage of students involved in a violent incident at the school and the percentage of students who report being happy in the school, respectively. I then aggregate the log of equation (8) across individuals for each cohort t to construct the complete likelihood and to estimate parameters of the utility specification via maximum likelihood for each year. I assume ζ_{ij} is i.i.d. and follows an extreme value type I distribution. Standard errors are calculated using a bootstrap clustered method at the choice set level (i.e. the primary school).

5 The Effects on Parental Response

Before examining parental responses to the information disclosure, I assess whether there is sufficient variation between the different schools within the choice sets, for each of the school attributes examined. Such variation is a necessary prerequisite for the information on the attributes to be relevant and important to parents. As can be seen in panel A of Table 2, for the entire sample, the average difference between the best and worst options in the choice set is 0.6 standard deviations (SDs) for average school test scores, 1 SD for the percentage of students involved in violent incidents, and 0.9 SDs for the percentage of students who report happiness

[15] For a robustness test related to the independence of irrelevant alternatives assumption required for the conditional logit estimation and a more straight forward interpretation of the coefficients related to the effect on increased probability, I also estimated the main outcomes using the linear probability model, the results of this alternative specification are similar both in significance and in comparison to the marginal effects of the logit model specification, as can be seen in panel B of appendix Table A2.

with the school. For the sub-sample of choice sets with above-median differences between the 'best' and 'worst' school options for each attribute, the average differences are 1.2 SDs for test scores, 2.3 SDs for violence levels, and 2 SDs for satisfaction ratings, respectively. The joint distribution of the ranges for each attribute within the choice sets is presented in Figure 2. To further explore the residual variation for each of the attributes, I adopt a similar approach to that employed by Fisher et al. (2012). Specifically, I analyze the residual variation remaining for each of the primary attributes within the choice set, while also controlling for the presence of the other attributes. The results of this analysis are presented in Appendix Table A1. In this table, we observe that while the choice set fixed effect accounts for a significant portion of the attribute variation, the standard deviation, as well as the proportion of observations exhibiting meaningful residual variation, remain substantial. This holds true for the entire sample, as well as when examining sub-samples by choice set disparities and socio-economic status. These findings provide supportive evidence that there is sufficient variation and scope for parents to sort according to the different attributes if they wish to and have the relevant information. Furthermore, these findings suggest that any variations in the response are unlikely to be primarily driven by differences in residual variation.

5.1 Parental Response to School Level Information Disclosure

Figure 3 shows that the information disclosure had an effect on parental response relating to the information on school satisfaction and violence levels. The effects were particularly pronounced when examining choice sets with above median disparities in ratings between the middle school options (i.e. choice sets for which the rating differences between the 'best' and 'worst' options were higher). This suggests that information on the publicized school attributes played a role in parental school choice decision-making, implying that parents place value on these attributes.[16] The Figure presents the effects when estimating the coefficients from equation (7), along with their 95% confidence intervals. For the entire sample, the information disclosure had an added increase of 0.14, 0.07 and 0.11 in the three years following the disclosure, respectively, relative to the observed log-likelihood increase of attending a school with a 1 SD higher satisfaction ratings in the baseline (last pre disclosure year). For the school violence rating information, the added effect was an increase of 0.05, 0.07 and 0.03 in the log-likelihood for the cohorts in the three years following the information disclosure, respectively. When looking at choice sets of above median disparities in ratings, we observe stronger results for both the satisfaction ratings (0.56, 0.48 and 0.54 for 2013, 2014 and 2015,

[16]The entire effect is unlikely to be solely attributed to saliency driven by the media, as another measure similarly highlighted by the press, teacher fatigue, did not have a significant impact on parental responses for any of the specifications.

respectively) and violence (0.21, 0.17 and 0.13 for 2013, 2014 and 2015, respectively).[17]

The magnitude of the results presented in the figure depends somewhat on the choice of the omitted year in our estimation. In Table 3 I present regressions of the differences between periods before and after the information disclosure, with the before years and after years stacked into two separate groups. I find significant differences for both the entire sample and especially for the above median differences sub-sample. In Table 3 I further demonstrate that parental response is higher in choice sets with above median differences in ratings compared to choice sets with below median differences (The response is larger by 0.457 for satisfaction and is precisely measured and larger by 0.076 for violence and is only marginally significant at the 10% level). This finding provides further support to the idea that large disparities between schools in the attributes create stronger incentives for parents to choose the schools based on these attributes.[18][19]

Interestingly, as illustrated in Figure 3 and Table 3, the findings related to the average test score information, while similar in magnitude for the entire sample, exhibit notably smaller effects within the sub-sample characterized by above-median differences in test scores. This result could be explained by any combination of the following reasons. First, parents might

[17] While the results present both visual and statistical supportive evidence for the general absence of pre trends in parental response, recent research has highlighted that tests of pre-existing trends have several limitations (Roth, 2022). In order to further test for the robustness of the effect to the existence of pre trends and support the causal identification of the impact of information on parental response, I employ the sensitivity analysis method proposed by Rambachan and Roth (2023). This approach formalizes the intuition motivating pre-trends testing by constructing robust confidence intervals under the restriction that the magnitude of the post-treatment violation of parallel trends can be no larger than a constant M times the maximal pre-treatment violation. In Appendix Figure A2 I show that the conclusion for a significant average causal response by parents is robust to deviations of at least 25 percent of the maximal pre treatment effect, for all the main effects discussed in the paper.

[18] In my main specification I choose to use the range of years from 2010 to 2015, consisting three pre-treatment and three post-treatment years. Several considerations influenced this choice. First, since I use constant attribute information from the last pre treatment measurement for each school to avoid issues of endogeneity, Expanding the number of years in the pre- and post-periods would likely introduce additional measurement error because the correlation between our measured attributes and the current-year attributes diminishes with time. Second, a broader time frame could capture other policies and institutional changes that might bias the results. Lastly, to select the final sample of students for analysis, I require all cohorts of students from the same primary school to have the same choice set for every year in the sample to avoid potential endogeneity issues related institutional changes in choice sets. This requirement means that each year I add for the pre- or post-treatment to our estimation, decreases the sample size of choice sets due to changes in registration zones and the opening and closing of middle schools. My chosen threshold for the optimal number of pre-treatment years was to lose no more than 30 percent of the sample of choice sets, which correspond to keeping three pre treatment years. Adding an additional pre or post treatment year would decrease the sample of schools by 33 and 34 percent, respectively, relative to the one pre treatment and three post treatment years. As demonstrated in Panel C of Appendix Table A2, results are qualitatively unchanged with the addition of an extra pre- (2009) and post-treatment (2016) years to the sample, although the coefficients are somewhat smaller, and standard errors a larger, possibility due to the issues notes here.

[19] In Appendix Figures A3, A4 and A5 I also present the distribution of the stacked before and after regression estimates for each municipality with an MLE solution, separately. The Figures further illustrate that the effect seems to be stronger for choice sets with above median differences and suggests that the results do not seem to be driven by outliers.

not value test scores as much as as satisfaction and violence levels when evaluating which school to choose. Second, parents may have possessed prior implicit information regarding test scores, or test score differences between the schools in the choice set. The official information they received may not have prompted substantial updates to their beliefs concerning this attribute, unlike the case of satisfaction and violence levels which might have been less accessible without the information disclosure. Third, the change in saliency following the press coverage may not have been as pronounced for test scores compared to other attributes. In the next section, when discussing the heterogeneous response by SES, I provide supportive evidence that these proposed explanations are complementary in explaining the disparities in responses among different population segments to various school attributes. In general, any combination of these reasons would still suggests that parents highly value information disclosure regarding alternative measures of school quality, such as satisfaction and violence levels, in comparison to the more commonly discussed measure of test scores. This heightened valuation is especially pronounced for choice sets with large disparities across these attributes.[20] Furthermore, additional support for the significance of school atmosphere information to parents can be drawn from a 2014 survey conducted by the Division of Evaluation and Measurement of the Ministry of Education (RAMA). This survey gathered responses from 787 parents and probed their considerations when selecting a school. The findings reveal that 65 percent of parents rated school atmosphere as an important determinant, a percentage on par with the 61 percent who considered academic achievement and the 65 percent who prioritized geographical proximity to their residence. These three factors emerged as the most highly ranked determinants in the survey.

Next, I provide an interpretation for the magnitude of the effect size and compare it to other studies in the literature on school quality information disclosure. The average cohort size for 6th graders in a primary school is 69.44. Examining the entire sample (sub sample with above median difference in the choice set), in the years following the information release, the marginal increased probability at the mean was approximately 3 percentage points (11 percentage points) which translates to an average shift of around 3 (8) students in each primary school choosing a middle school with a 1 SD higher satisfaction ratings. When considering the response to violence ratings, the marginal increased probability at the mean was slightly above 1 percentage points (3 percentage points), which translates to an average shift of nearly 1 (3) students in selecting a middle school with a 1 SD higher ratings when examining the

[20] An alternative explanation could point to differences in attribute variation between the schools within the choice zone. Specifically, satisfaction and violence levels might exhibit higher levels of variability among school options compared to test scores, potentially creating stronger incentives for parents to base their decisions on these attributes. However, this hypothesis is less likely to drive the results. As presented in the beginning of this section, the disparities in scores, violence, and satisfaction ratings between the various school options within the choice sets are comparable for both the entire sample and the sub-sample with above-median attribute differences.

entire sample (sub sample with above median difference in the choice set). A 1 SD increase in satisfaction and violence ratings corresponds to an approximate 8 and 3 percentage points increase in students who report being satisfied and free from exposure to violence in middle school, respectively. This would translate to an average of about 6 and 2 additional students in a middle school cohort who report being happy in school and that don't experience violence, respectively, or to an increase of about 10 and 3 percent compared to the mean of 75 percent and 88 percent of students who are happy and don't experience violence in middle school.

These results are economically and statistically significant, providing an important indicator given that the information intervention in this context was not as salient as in previous interventions. In our setting, information was not directly provided to parents via letters, rather, it was organically publicized in the press. This provides a more natural setting of information disclosure which includes parental search costs. In the previous literature, Hastings and Weinstein (2008) examined the effects of targeted information on test scores to households of students from under performing public schools in Charlotte, North Carolina, as part of the No Child Left Behind Act. The study found that, following the receipt of letters containing explicit information about test score averages for schools within the choice set and statements regarding the under-performance of the default school, approximately 16 percent of parents responded by choosing to attend schools different from the default school, schools with an average test scores approximately 1 SD higher. In a randomized control trial, Campos (2023) provided parents with letters containing information on the schools' VA measures and the average test scores of incoming students for each school in their choice set within the Los-Angeles public school system. He finds that, relative to the control group, the treatment group increased their top ranked school choice by between 5 and 9 percentile points for the VA measure, with no significant changes in the preferences related to peer quality.

5.2 Heterogeneous Response by SES, Gender and Immigration Status

Next, I explore how the response to information interacts with various student characteristics. I estimate regression (7) separately for different subgroups categorized by high and low SES levels, gender and immigration status. Differences in the response to information can be attributed to several factors. First, specific groups, such as high or low SES parents, may place different values on the importance of various school attributes in contributing to their child's success and well-being. Additionally, these groups might differ in the (perceived) sensitivity of their child to each school attribute, represented by the κ parameter in equations (3) to (6). Variation may also exist in the amount of prior information that parents possess regarding school attributes or the differences between schools in their choice set with respect to these attributes, which can lead to differences in the degree of updating following the information disclosure. Lastly, households from certain groups might find it easier to make

trade-offs on other school-student matches, such as school distance, when information about a perceived better school becomes available.

To estimate the heterogeneous effects by SES, I use parental education as a proxy for SES. In order to divide our sample into high and low SES levels I assign households to be high SES if at least one of the parents had more than 12 years of education and to the low SES group otherwise, as is commonly done in the literature (Entwislea and Astone, 1994; Guryan et al., 2008). As can be observed from Table 1, high SES students make up approximately 36 percent of the entire sample and are represented in all municipalities and all but 7 middle schools and 1 primary school. Low SES students make up around 64 percent of the sample and are present in all the schools analyzed. Figure 4 indicates that lower SES households tend to be more responsive to information related to school violence and satisfaction levels. Conversely, we do not consistently observe significant responses among higher SES households. Table 3 further shows that there are large differences in parental response between low and high SES households, when looking at the analysis which combines the before and after years into two separate groups. These differences are especially pronounced for choice sets with above median differences in the various attributes. For this subsample of choice sets, at the mean, the marginal increased probability of attending a school with a 1 SD increase in school satisfaction and violence levels is 10 and 5 percentage points higher, respectively, in the years following the disclosure. With respect to the average test score information, as shown in Figure 3 and Table 3, there is a general lack of response to the information, with no significant differences between the socio economic groups.

The general lack of response by higher SES households is likely related to their pre sorting to schools with better attributes within their choice set. In Table 2 I present evidence regarding the probability of selecting a school with better attributes in the years preceding the information release, as estimated by the model. Panel B reveals that, for choice sets with above median differences (where most of the effect is observed), higher SES households exhibit an increased probability of attending schools with better test scores (0.0788), less violence (0.329) and more students satisfaction (0.454). Conversely, there doesn't appear to be a similar positive selection among lower SES households, even in choice sets with large disparities. These results suggest that higher SES households were more likely to possess accurate and credible information about the schools in their choice set even prior to the public information disclosure, consistent with previous research (Hoxby and Avery, 2012; Schneider and Buckley, 2002; DeLuca and Rosenblatt, 2010; Ben-Porath, 2009).

While the differences in prior information might explain some of the heterogeneity in the response between high and low SES households, they cannot explain the disparities between the significant response to the violence and student satisfaction ratings and the lack of response to standardized test scores. These findings are consistent with the idea that the response to

information depends on the perceived sensitivity of the student to the school attributes (κ). Students from lower SES households might be more vulnerable to engaging in violent behavior or being negatively influenced by peers involved in violence. They might also be more sensitive to school attributes impacting socio-emotional well-being due to the lack of stability and parental support, which lower SES households are more prone to experience. Consequently, these factors can exert a stronger influence on student achievement compared to the academic level of their peers, which is proxied by information on the average standardized test score at the school (Jackson et al., 2023; Cunha et al., 2010; Lavy et al., 2012a). The results are less likely to be driven by the ability to make trade-offs between idiosyncratic factors and school attributes, as the limitations associated with those trade-offs should remain consistent across the different school attributes. These limitations might be generally more pronounced for lower SES households, potentially attenuating the findings related to their response.

Furthermore, while gender differences in children's responses to school quality and peer characteristics have been observed in the literature (Lavy et al., 2012b; Jacob, 2002), prior studies on information disclosure have not detected gender-related differential responses to information about test scores (Hastings and Weinstein, 2008) or value added measures (Ainsworth et al., 2023). In panel D of Table 3 I present suggestive evidence that households of male students exhibit a stronger response to information related to school violence levels. This finding is consistent with the previously discussed idea that the response to information may depend on the perceived sensitivity of the student to the school attribute. Male students might be particularly affected by the level of violence (Lavy and Schlosser, 2011). In Panel E of Table 3 I also provide suggestive evidence that households with at least one immigrant parent, display a reduced response to the information disclosure compared to their non-immigrant counterparts. This difference could potentially be attributed to the idea that immigrant parents are less likely to be exposed to the information disclosure as they are less likely to read the native language publications which highlight the school level attribute information. This potential information friction highlights the need for specific interventions to ensure equitable access to information (Corcoran et al., 2018).

5.3 The Connection Between School Attributes and Value Added Measures

So far I have presented evidence that schools in households' choice sets vary across various school attributes. I further demonstrated that parents respond to information disclosure by selecting into schools according to these attributes, indicating that they perceive them as important indicators for some measures of school quality. In the following section, I explore whether these perceived measures are related to a more traditional and commonly used measure of school quality: the value-added measure. To evaluate the VA for each middle school, I estimate a standard VA model, as described in equation (1). This model is based on end

of high school matriculation test scores, while controlling for observable school and student characteristics, including lagged test scores from primary school. I then examine the connection between the different school attributes and VA by estimating at the correlation between them.

Table 4 displays the correlation estimates for the connection between the various measures. The correlation results for our three attributes reveal associations in the expected direction. Both student satisfaction and test scores are positively correlated with each other and negatively correlated with increased violence. While these measures exhibit correlations, they are of moderate size, particularly for the violence attribute (-0.34 with satisfaction and -0.14 with test scores, respectively). This allows enough independent variation for the measures to represent different aspects of school quality.[21] Concerning the correlation with the VA measures, only violence levels display a strong correlation with the VA measures, with a correlation score of 0.25. Satisfaction and middle school test score levels were weakly correlated with VA measures and in the opposite direction (-0.06 and -0.05, respectively). Interestingly, without controls for primary school test scores when calculating VA measures, the correlation of VA with violence levels remains consistent, though the correlation with satisfaction levels and test scores would have appeared strongly positive (0.19, 0.46 and 0.6, respectively). These findings suggests that, after controlling for the abilities and characteristics of the incoming student population, only indicators of violence levels signal a quality of the school which can be linked with future improvement in educational outcomes. Satisfaction, and interestingly, even school average test scores, were not reliable indicators quality that can enhance high school educational success, supporting related findings in the literature (Fabregas, 2023; Campos, 2023).[22]

Next, I proceed to investigate whether the information disclosure about the various school attributes and the subsequent parental response led households to select schools with higher VA. I estimate an equivalent of equation (7), replacing the school level attribute measures with the school VA measure. In Table 5 I first show that, while I do not find an effect for the entire sample, there was a significant increase in the probability of attending schools with higher VA for the subset of choice sets with high disparities in school violence levels. This observation aligns with the earlier findings regarding the stronger effect in choice sets with large disparities and the positive correlation between violence levels and school VA measures.

[21] Jackson et al. (2020) also find that student survey information on socio emotional indicators are a reliable measure of real school impacts and have strong predictive power for both academic and non-academic future student success. Lavy and Schlosser (2011) also find that the same survey questions used in this study, which describe the quality of the school atmosphere, are strongly connected with student academic success.

[22] I also examine an alternative estimating of the VA measure, which includes a fixed effect of the choice set, allowing a more direct examination of the connection between the different attributes and the school quality options for each household. The results of this estimation are consistent with our main measure, albeit expectedly weaker, as it controls for more of the variation in quality differences between schools. The correlation between this VA measure and violence, satisfaction and test scores is 0.15, 0.04 and 0.04, respectively.

An additional driver for the increased positive selection into higher VA schools might be that the information disclosure prompts households to reevaluate their school choices, invest time and effort in finding the best option, and ultimately choose a school with higher VA beyond their selection based on the school attributes I examined.

In Panel B I demonstrate that most of the effect is driven by positive selection among lower SES households. This result is consistent with the earlier observation that lower SES households were more likely to respond to the school-level information on violence and satisfaction.[23] This finding provides evidence of increased selection of lower SES students into better schools following the information disclosure, which could have significant implications for the policy's role in enhancing social mobility.

The findings in this subsection point to the potential role and benefits of providing information on a range of school attributes beyond test scores or even VA measures to households with diverse characteristics. First, as VA estimates can be more challenging to measure and comprehend, alternative measures like student-reported school atmosphere indicators might serve as suitable proxies and be more accessible for parents to understand. Moreover, even if VA measures are available, alternative measures such as violence and satisfaction levels appear to hold importance for parents, capturing aspects of school quality that standard VA (and test score) measures cannot, pointing to the multidimensionality of school quality (Beuermann et al., 2023; Riehl et al., 2018). These qualities may involve creating a safe and positive environment where students can thrive and develop, a quality valued by parents and which can contribute to long term student success that cannot be fully captured by high school test scores alone (Jackson et al., 2020, 2023).

In order to account for the potential bias arising from incorporating a noisy estimated measure of school VA in the subsequent estimation presented in this sub section, I implement a Bayes shrinkage estimation strategy and construct an unbiased measure of school VA that accounts for noise in the measurement. Under this approach, the noisy measure of school VA is multiplied by an estimate of its reliability. The reliability of a noisy measure is the ratio of signal variance to signal variance plus noise variance. Thus, less reliable measures are shrunk back toward the mean of the distribution of the school VA measure.[24] I find

[23] In relation to the findings that higher SES households are more likely to select into schools with better attributes even prior to the public information disclosure, similar patterns emerge when examining school Value Added (VA). As presented in Table 2, Panel B illustrates that students from higher SES households exhibited a slightly higher increased log likelihood of attending a school with a 1 SD increase in school value added. This observation is in line with previous research, such as the work by Ainsworth et al. (2023), which suggests that households with higher-ability students, a correlate of SES levels, tend to possess more accurate beliefs about the Value Added and test score selectivity of the schools in their choice set compared to households with lower-ability students.

[24] Following Morris (1983) and the teacher value-added literature (for example, Kane and Staiger (2008)) I construct the Empirical Bayes (EB) shrinkage factor for the VA of middle school i by the ratio of signal variance to signal variance plus noise variance of school i. In a similar way to the teacher value-added literature, I assume that the measure of school VA bias includes an error component. Thus, estimating school effect on students'

a correlation of 0.95 between the unadjusted and Bayes corrected VA measures, indicating that measurement bias from using an estimated school VA measure is unlikely to explain the results. In Appendix Tables A3 and A4 I reproduce all the results related to the VA measures, using the Bayes corrected measures. I find no significant differences compared to the results using the unadjusted measure, supporting the credibility of the findings.

5.4 Effects on Socio-Economic Integration

Up to now, I have presented evidence indicating that lower SES households respond to information by choosing schools with higher student satisfaction and lower violence levels, leading to attendance at schools with higher VA. Next, it would be of interest to explore whether the observed student shifts had any implications for social integrating. To provide suggestive evidence on this, I estimate the level of social integration by measuring the difference in the percent of high SES peers that each student from the high versus low SES group has in his school cohort. This is a commonly used measure (Chetty et al., 2020; Hoxby and Turner, 2019), which has also been shown to have an effect on social mobility (Chetty et al., 2022).

I first examine the correlation between the various school attribute measures and the percentage of high SES students in the school. I find a strong correlation with test scores (0.59) and the student satisfaction measure (0.46), but a weak connection to violence levels (0.02). Interestingly, there is a positive correlation with the school VA measure (0.17), providing further support for the potential positive effects of having high SES peers on achievements, found in the literature (Chetty et al., 2022).

Next, in Table 6 I estimate whether there were any differential shifts in average integration levels for middle schools located in regions with school choice, compared to those without, following the information disclosure. In Panel A, I present the gaps in the percentage of high SES peers in the middle school cohort between students from high and low SES households, separately for the households with school choice and those without. As the group of households with choice and the group without come from different municipalities, Panel B implements an adjustment procedure, similar to Hoxby and Turner (2019), to identify the effect on school integration separately from municipality integration. This involves dividing the share of each SES group in a school cohort by the equivalent share in the municipality to calculate the segregation levels remaining after adjusting for the relevant municipality pool. In both cases, there is no evidence to suggest that the information disclosure led to changes in integration levels. This outcome is plausible given that the strongest correlation between the ratio of high

outcomes enables separation of the signal variance (variance of school effects) and noise variance of school i (variance of the residuals for school i). The EB estimate for each middle school is a weighted average of the school's estimated effect and the mean of school VA estimates, where the weight is the EB shrinkage factor. Implementing this methodology, the less reliable estimates of school VA (those with a large variation in estimated residuals) are shrunk towards the mean of school VA estimates.

SES students in schools was with test scores, a measure that did not elicit a strong response, and a smaller correlation with the measure of violence levels, which did produce a stronger response from lower SES households.[25]

An interesting finding from Table 6 is that schools in municipalities with school choice policies have significantly lower gaps between high and lower SES students in terms of the percentage of high SES peers, compared to schools in municipalities without school choice policies. This finding is further supported by the narrower gaps observed for the choice group when considering school SES segregation beyond the municipal level, as shown in panel B. This provides suggestive evidence, although without causal identification, that, in certain settings, school choice policies may contribute to increased SES integration in schools.[26]

6 School Response

Thus far, we have focused on household preferences and responses to the information disclosure. To attain a more complete characterization of its potential market-level effects, in this section I examine how schools responded to the potentially increased accountability in a competitive school choice setting. I first employ a difference-in-differences strategy to estimate the differential effect of the information disclosure on schools in regions with school choice for the set of publicized attributes.

$$Y_{jt} = \alpha_j + \alpha_t + \sum_{k=-3}^{3} \beta_k Choice_j \times \mathbf{1}\{t - 2012 = k\} + \lambda X_{jt} + \zeta_{jt} \tag{9}$$

where Y_{jt} is the middle school rating of student satisfaction, school violence or the average GEMS test score for middle school j is year t. α_j and α_t denote middle school and year fixed effects, respectively. $Choice_j$ is an indicator for whether school j is in a region with school choice, and X_{jt} is a vector of school characteristics that vary over time, including the number of female and male students, and various indicators of the socioeconomic and ethnic composition of the students. [27] β_k represent the residual differences in outcomes between middle schools in regions with school choice and those without in period k . Differences when

[25] An alternative exercise, which replaces the school-level attribute measures with the ratio of high SES students in the school in equation (7), also does not provide evidence that households were more likely to attend middle schools with a larger percentage of higher SES students following the information disclosure. Results available from the author.

[26] The literature on the effects of school choice on socioeconomic segregation levels, mostly finds a negative influence on social integration (Musset, 2012). An alternative explanation positing that municipalities with a stronger commitment to integration and/or higher existing levels of integration may be more inclined to promote school choice policies, is a plausible alternative explanation to the increased integration in municipalities with school choice.

[27] These indicators include the decile representing the average economic status of the school's student composition, compiled by the Ministry of Education, as well as measures of parental education and ethnic origin.

$k > 0$ represent the school response, while differences when $k < 0$ would indicate a potential threat to the parallel trends assumption. $k = 0$ is the omitted baseline period, representing the last pre disclosure year.[28] u_{jt} is a normally distributed mean zero residual. Standard errors are clustered at the school level.

Figure 5 displays the results from estimating equation (9). In the third year following the information disclosure, we observe a significant differential increase of 5 percent (0.6σ) in the percent of students reporting satisfaction at school, along with a significant differential decrease of 3 percent (1σ) in the percent of students reporting exposure to violence at school. I do not observe a significant differential change in GEMS test scores during the observed period (¡0.1σ). This may be due either to a lack of ability or motivation to improve standardized test scores, or because improving these scores was already a priority prior to the information disclosure, leaving little room for further improvement.

The observed changes in rating may be attributed to schools' responses to increased accountability pressures in a competitive environment. Alternatively, compositional changes and match effects resulting from household responses to the information might also explain some of the observed effects (Abdulkadiroğlu et al., 2020; Bau, 2022). To examine the role of compositional changes, I control for time-varying indicators of student composition in equation (9). As shown in Figure 5, the results remain virtually unchanged after including these school controls, suggesting that compositional changes are unlikely to be driving the results.[29]

Next, in order to examine whether the effects differ between lower- and higher-performing schools, I explore heterogeneities in responses across the distributions of the different attributes. Following Chernozhukov et al. (2013, 2020); Campos and Kearns (2022), I estimate unconditional quantile treatment effects to examine the effects at different deciles of the distribution. I first estimate the cumulative distribution functions for satisfaction, violence, and test score ratings for schools in regions with school choice, as well as a counterfactual distribution, and then invert each to obtain the implied unconditional quantile treatment effects. As shown in Figure 6, improvements were generally evenly distributed across the rating spectrum, although schools with higher initial violence ratings experienced slightly larger improvements.

The increased accountability based on measures of student satisfaction, violence levels, and test scores on a specific exam might lead schools to adopt response strategies such as an increased focus on student experience and discipline, along with "teaching to the test" strategies and inefficient budget reallocation (Popham, 2001; Rouse et al., 2013). Given these potential response strategies, an important question is whether school response might compromise academic learning. To address this issue and examine the potential effects across the

[28] This setting is a canonical difference-in differences design, thus results are not sensitive to two-way fixed effect design biases introduced in recent literature (Roth et al., 2023)

[29] Although I include a wide array of student composition attributes, unobserved compositional and match effects not captured by the controls might still influence some of the observed effects.

distribution of school performance, I apply a similar procedure using unconditional quantile regression analysis to estimate the impact on school value added—a proxy for the school's ability to enhance student academic achievement. As shown in Figure 7, high-value-added schools in regions with school choice experienced a differential decrease following the information disclosure, suggesting that accountability-driven school strategies may partly come at the expense of student academic improvement.

The findings in this section underscore the importance of information in driving school changes motivated by competitive pressures. Another novel contribution of our study is demonstrating that a diverse set of school indicators can encourage improvements in key non-academic school attributes. Our results also highlight potential pitfalls of school competition and the need for well-designed incentive schemes and rigorous monitoring to prevent long-term adverse effects on student outcomes.

7 Additional Findings on School Life and Information Networks

7.1 Other Survey Questions

I have thus far focused on the effects of information related to the attributes featured in the *'Israeli Education Map'* project publicized by the press and the popular apartment seeking site. In the GEMS survey information, there where many other questions regarding different aspects of school life.[30] Although these questions were not highlighted following the information disclosure, examining them, their connection to VA measures, and parental response to them has value for several reasons. First, considering the presented evidence supporting the idea that households with diverse characteristics might value different school attributes based on their child's needs, there is value in publicizing a wide array of school attributes covering various aspects of school life, to allow parents to make an informed choice. Moreover, linking these attributes to school VA measures will allow school administrates and policymakers to target improvements related to an important aspect of school quality. Furthermore, evaluating the response to the less publicized measures serves as a robustness check on the causal interpretation of the response to the publicized attributes. As a lack of response to these measures, contrasted with the significant response to the publicized measures, would support the idea that the effect is driven by the information reveal as opposed to other unobserved factors.

To have a better representation of the way the student survey questions might capture

[30] Parents could access these measures following the information disclosure, albeit in a less accessible manner, by logging into the Education Ministry website, searching for each school and examining the official detailed report.

different aspects of school life, I conducted a factor analysis to unveil its latent factors. Figure 8 displays the factor loadings for the optimal number of factors, which are those with eigenvalues exceeding 1 according to the Kaiser-Guttman method (Kaiser, 1960). A possible interpretation of the factors is the following. **Factor 1**, is associated with questions related to teacher feedback, expectations and fairness as well as how much teachers care about the students and how much work is put into keeping them safe. This factor reflects students' perceptions of their teachers' performance and their relationships with them. **Factor 2** pertains to students' responses regarding their frequency of tardiness or absence from school, potentially indicative of school attentiveness, discipline, as well as the stability in the life of the students in the school. **Factor 3** encompasses questions related to happiness (including the question examined in the paper on school satisfaction) as well as questions related to feeling safe and teacher fairness. This factor represents students' overall feelings of happiness and security in school. **Factor 4** is linked to questions about to the extent and strength of students' relationships with their peers within the school, while **Factor 5** is associated with questions describing a threatening and toxic environment (including the question examined in the paper on whether the student reported being kicked or punched in school during the last month).

Next, I investigate the relationship between these latent factors and school quality, as measured by the value-added (VA) estimates presented in earlier sections. Table 7 displays the correlations between the different factors and VA. Results show that these factors exhibit a strong correlation with VA, indicating their contribution to school quality. I then incorporate the factors into the estimation equations for the discrete choice model in order to estimate parental response to them. Figure 9 reveals that there was no significant response following the information disclosure regarding these measures.[31] This overall lack of response is not surprising and speaks more to the importance of the salience of information due to its publicity as a necessary condition, rather than reflecting a lack of value these attributes hold for parents. Additionally, the absence of a response to the less publicized measures provides supportive evidence for the causal interpretation of the effects of the information disclosure on parental response to the publicized measures. This is because other potentially omitted variables that might have caused a similar response would likely have affected the response to the less publicized measures in a similar fashion.

These findings hold importance for several reasons. First, the factor analysis is valuable in its own right as it unveils and facilitates an interpretation of the underlying concepts of student surveys. These concepts are also evidently linked to school value-added and may

[31] When replacing the factors which contain the violence and satisfaction ratings with the specific publicized questions related to them, I find that parental response to those measures remains strong (results are presented in appendix Figure A6). This suggests that the lack of effect relating to the factor is unlikely to be driven by lack of residual variation in the factors.

represent different facets of school quality not captured by test score information (Jackson et al., 2020). Furthermore, in most studies, information interventions are designed to be as salient as possible to achieve the desired impact. However, the signal sent could vary in strength or scope. The contrasting responses to the publicized measures and the lack of response to the remaining publicly available attributes highlight an important consideration. External interventions, like media coverage and practical use by websites, might be sufficient to disseminate information to parents of all SES levels. Yet, ensuring accurate measurement of the proper attributes and monitoring the emphasis placed on specific information is crucial. Policymakers may need to consider potential interventions if these measures fail to accurately represent schools and, consequently, shape parental responses as intended.

7.2 Networks of Information Sharing

An essential aspect to consider when analyzing interventions related to information disclosure is to explore how information is disseminated (Banerjee et al., 2021; Campos, 2023; Golub and Sadler, 2017). In the current context, it would be of interest to examine whether, in addition to direct exposure to the press publications, information was also transmitted through informal parent networks. This notion is further motivated by the findings of a parental survey conducted by the Division of Evaluation and Measurement of the Ministry of Education (RAMA) in 2014. The survey, which queried 787 parents about their considerations when selecting a school, revealed that a significant proportion of parents mentioned recommendations from other parents (52 percent) and the desire for their children to attend the same school as their friends (54 percent) as important determinants when making their school choices.

In related settings of schools choice, Facchetti et al. (2024) found that organized information sharing sessions between primary school and middle school parents increased the likelihood of parents choosing to attend middle schools represented in the sessions. They also observed spatial spillovers in information sharing, where the increased probability of attending the represented middle schools extended beyond the directly informed households. In a high school choice context, Campos (2023) documents the existence of information spillovers relating to school VA measures from households receiving school quality information to their counterparts in the same school. These spillovers influenced preferences towards higher VA schools for both the directly informed households and indirectly treated households due to information sharing.

To gauge the existence of such informal parent networks, I examine groups of parents with a higher propensity to establish informal connections and share information among themselves. Such networks may include parents of students who belong to the same class or school, share a common country of origin, and speak the same native foreign language (e.g., immigrants

from Russia, Ethiopia, or the US).[32] I then investigate whether there are discernible shifts in the clustering of students from the same group selecting the same middle school subsequent to the information release, using the Herfindahl-Hirschman Index (HHI) to estimate the degree of concentration among middle school options within each choice set.

Due to the massive incoming immigration to Israel from former Soviet Union countries in the 1990s, a significant portion of our sample (13.3 percent) comprises households in which at least one of the parents immigrated from a former Soviet Union country, allowing a reliable estimation of the changes in concentration levels.[33] If information on school level indicators was shared within this group of immigrant households in the same classroom, two conditions would likely be met: 1) Households within the same primary school class from this group would be more likely to choose the same middle school option following the information reveal.[34] 2) Classroom groups displaying this heightened concordance in school selection would likely exhibit an increased likelihood of choosing a middle school with better revealed attributes, in comparison to prior cohorts.

In Table 8 I present evidence related to the shifts in middle school enrollment concentration following the information disclosure using the HHI.[35] In panel A I estimate the mean change in HHI for each classroom in each primary school for the sub sample of students with Soviet born parents. I find a significant increase of 0.135 standard deviations in HHI levels in the period following the information disclosure compared to the pre period. To explore variations beyond the average effect, in Figure 10 I present results for the cumulative distributions of classroom HHI separately for the pre and post periods. Using the Kolmogorov-Smirnov test, I find that the two distributions are significantly different from each other and that most of the upward shifts occur in the middle range of HHI values. In panel B of Table 8 I examine whether the changes in concentration observed for households with Soviet-born parents are unique to this group, relative to the entire sample of students. By interacting a dummy variable for the post-disclosure period with a dummy variable representing Soviet-born parents, I find that for the rest of the sample, there are no significant shifts in HHI following the information disclosure,

[32] See (McPherson et al., 2001) for evidence and a discussion on homophily in information networks.

[33] No other distinct group accounts for more than 2 percent of the sample, precluding a reliable estimation including other groups.

[34] An alternative prediction could be that households from this group, who previously tended to select the same middle school to remain with their friends, might now, after the information disclosure, be more inclined to choose schools based on their individual values or preferences, which could differ among parents. In this scenario, the information disclosure could reduce the likelihood of them choosing the same school. This alternative prediction is not consistent with the findings, which show an increased concentration in middle school choice.

[35] To calculate the HHI for each classroom in each of the primary schools in the choice sample, I employ the following method: 1. For each year and from each primary school classroom, I estimate the share of students choosing to attend each of the middle schools in the choice set. 2. Then, for each year and for each primary school classroom, I calculate the HHI by summing the squares of the shares for each middle school choice, as calculated in step 1. An illustration of the HHI calculation is presented in Appendix figure A7.

while I observe a significantly higher shift for the Soviet born group. Furthermore, I find that the concentration increases for the subsample of households with Soviet born parents are lower when examining groups at the school level or municipality level compared to the class level (smaller by 21 and 76 percent, respectively). This provides further support for the existence of information sharing networks, rather than an alternative explanation of a general, differential increase in response for households with Soviet born parents.

After observing that households in the same classroom with Soviet-born parents are more likely to choose the same middle school following the information disclosure, I investigate whether this choice is associated with the disclosed school-level information. In Panel C of Table 8, I estimate, for the sub sample of students with Soviet-born parents, for each primary school class, the shift in the share of attendance of the first ranked middle school choice in the choice set in test scores, and violence and satisfaction ratings. I find that, compared to groups with below median shifts in HHI, the groups with above median shifts experienced a differential increase of almost 7 percent in the share of students choosing the best rated option in their choice set in term of student satisfaction. There were no significant shifts related to the other attributes.

The findings presented in this subsection provide suggestive evidence for the existence of a network of information sharing relationships based on similar ethnic and cultural ties, which increases the likelihood of the members in the network selecting schools based on the disclosed information. To further support this idea, I examine whether the number of peers from the same ethnic group in the classroom increases the probability of households selecting schools with better publicized attributes post information disclosure. The likely channel in this case would be that a higher number of intragroup peers increases the probability of exposure to information, which in turn increases the likelihood of response. In Table 9 I present results supporting this notion. The table demonstrates that households with Soviet-born parents are more likely to select school with lower violence and higher satisfaction ratings post information disclosure if they have a higher number of Soviet-born peers in the classroom. In contrast, the effect of the number of native-born peers on this response is comparatively weaker. Conversely, for native-born students, the effect appears to be mostly reversed, with a stronger influence observed for having a higher number of native-born peers. These results, which further bolster the notion of information sharing based on ethnic origin, remain robust even after controlling for the total number of peers in the classroom and are more pronounced among the lower SES group, aligning with their generally heightened response to the information.

8 Conclusions

The rapid proliferation of school choice policies globally and in the United States in particular has fueled a growing debate regarding their societal impact (Neilson, 2019). Proponents argue that these policies hold the potential to enhance both equity and efficiency by affording all students, particularly those from disadvantaged backgrounds, the opportunity to select higher-quality schools. This, in turn, can stimulate competition among schools, motivating improvement in quality. Detractors, however, are wary of the potential exacerbated inequalities that may arise from additional student sorting based on attributes such as SES, ethnicity and ability (Musset, 2012). At the heart of this debate lies a fundamental question: Will households across the SES spectrum, when presented with clear and comprehensive information about the available schooling options, respond by selecting schools in a way which can lead to better outcomes, increased equity in information and resources and encourage school improvements along dimensions which parents value. Prior research, which primarily focused on information provision directly related to academic school measures like average test scores and value-added measures, has found that a significant portion of households, particularly those from economically disadvantaged backgrounds, remains unresponsive to this type of information(Hastings et al., 2010; Ainsworth et al., 2023). This lack of responsiveness can contribute to increased segregation and diminish incentives for schools to improve, casting doubt on the effectiveness of information interventions in eliciting positive responses from lower SES parents (DeLuca and Rosenblatt, 2010; Fuller and Elmore, 1996).

In this paper I aimed to address this issue by examining the hypothesis that households might value school information on other attributes not directly associated with academic performance. The results indicate that households respond strongly to information regarding school violence levels and student satisfaction ratings. This response was especially pronounced for lower SES households, which subsequently led them to choose schools with higher value-added, thereby also enhancing their academic outcomes. This finding contributes to the literature by offering novel evidence on concrete, measurable school indicators that lower SES families positively respond to. It sheds light on the issue concerning the relatively muted response of lower socioeconomic status (SES) households to academic school information that could potentially enhance their children's prospects. It implies that households tend to prioritize information associated with attributes they perceive as having a more substantial influence in their children's lives. For families with lower SES, this emphasis might be placed on establishing a secure and encouraging learning atmosphere, rather than solely concentrating on standardized test scores.

In parallel with these household responses, our analysis of school response reveals that, following the information disclosure, schools in regions with school choice improved their

measured attributes by increasing student satisfaction and reducing violence ratings. The results further indicate that such school response strategies may come partly at the expense of academic learning, particularly for schools with high initial value-added. These findings on school response contribute to the literature by demonstrating both the potential benefits (improvements in key non-academic attributes) and trade-offs (reduced academic performance) that can arise from public disclosure of a diverse set of school indicators.

The magnitude of the effect of information may vary depending on the educational setting. For instance, in settings with potentially more severe violence and higher stakes for the effects of choice, such as the setting of high-school choice compared to middle schools. Regardless of the specifics of the setting, the overarching conclusions regarding the importance of publicizing a diverse set of school attributes, especially for equity concerns, should be tractable for various educational contexts beyond the specific one examined here.

In designing school choice policies and planning which school attributes to measure and emphasize, policymakers should consider the specific preferences of their target households and prioritize attributes that can lead to improved long-term outcomes for students. The methods and findings of this study offer valuable insights for informing such policies. They underscore the importance of assessing responses to various measures, as well as examining heterogeneous preferences beyond the average effect, particularly among households with diverse characteristics and needs. Additionally, this research highlights the significance of linking these measures with value-added metrics and the subsequent allocation of students to better-performing schools.

The Israeli context, characterized by fewer capacity constraints and limited student screening and private schools, offers a unique opportunity to accurately estimate the response to information by isolating the effect of the information on parental demand from school strategic supply side considerations. However, in settings with more pronounced school competition and as capacity constraints become binding over time due to increased demand for better schools, policymakers should consider broader education market dynamics that come into play (Neilson et al., 2019; Andrabi et al., 2017).

In light of our findings on school improvements in non-academic attributes and the associated trade-offs, future research should further explore key questions regarding how schools react to information disclosure on various school attributes. Can schools achieve sustained improvements in aspect such as violence reduction and student satisfaction, and what do successful strategies for achieving these improvements look like? Moreover, will these changes ultimately result in enhanced school quality across different value-added measures, aligning with the preferences of households and policymakers (Beuermann et al., 2023; Jackson et al., 2023)? Moreover, how can effective monitoring, competition, and information design incentivize the desired outcomes?

Finally, there is considerable value for policymakers, and to the literature, in designing information provision experiments which include a diverse range of school attributes and value-added outcomes. These experiments should consider potential variations tied to household characteristics, the strength of information signals, and the mechanisms for information dissemination, including media exposure and information networks (Haaland et al., 2023; Ben-Porath, 2009). By incorporating these features, such experiments can shed light on the biases and priors held by different groups of households. Furthermore, they can help identify the most effective interventions for improving household knowledge, access to better schools, social mobility, and short- and long-term outcomes across a wide spectrum of measures.

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Tables and Figures

Table 1: Descriptive Statistics

	All Students	Choice Sample	Above Median Violence Range	Below Median Violence Range	Low SES (≤ 12 years of education)	High SES (>12 years of education)
	(1)	(2)	(3)	(4)	(5)	(6)
A. Student's Characteristics						
Father's years of schooling	12.81	12.83	12.47	12.93	11.12	16.15
	(3.57)	(3.30)	(3.44)	(3.24)	(1.72)	(2.01)
Mother's years of schooling	12.68	12.69	12.36	12.78	10.81	15.63
	(3.81)	(3.57)	(3.64)	(3.54)	(1.83)	(1.97)
Number of siblings	1.75	1.66	1.53	1.70	1.70	1.40
	(1.42)	(1.36)	(1.44)	(1.34)	(1.42)	(1.02)
B. Student Outcomes						
Primary School Test Scores	64.44	65.52	65.70	65.47	61.97	72.47
	(18.35)	(18.16)	(17.73)	(18.29)	(18.25)	(15.33)
High-School Matriculation Scores	79.89	80.00	78.40	80.45	77.20	84.89
	(11.65)	(11.77)	(11.62)	(11.77)	(11.65)	(9.85)
Graduated High School	0.83	0.82	0.80	0.82	0.77	0.92
	(0.38)	(0.39)	(0.40)	(0.38)	(0.42)	(0.27)
C. Middle School Attributes						
Average Test Scores	59.05	60.35	59.87	60.48	58.97	64.03
	(11.02)	(9.88)	(11.28)	(9.44)	(9.59)	(8.18)
% of Students Satisfaied with School	0.73	0.75	0.75	0.75	0.74	0.77
	(0.09)	(0.08)	(0.09)	(0.08)	(0.08)	(0.07)
% of Students Reporting a Violent Incident in School	0.13	0.12	0.13	0.12	0.13	0.13
	(0.07)	(0.03)	(0.05)	(0.03)	(0.04)	(0.03)
Number of Municipalities	379	82	24	73	82	80
Number of Middle Schools	1,955	179	58	139	179	172
Number of Primary Schools	2,600	204	51	153	204	203
Number of Students	482,350	84,987	19,643	65,344	48,548	27,592

Notes: This table consists of the 2010–2015 cohort of 6th grade students rising to middle school in Israel. Column (1) contains sample means for all students, Column (2) contains sample means for the sample of students with middle school choice. Columns (3) and (4) contain the means for the sub sample of students where the difference in violence level ratings between to most and least violent schools in their choice set is above and below median, respectively. Column (5) and (6) contain, for the sample of students with school choice, the means for the sub sample of students for whom both parents have at most 12 years of schooling (we classify them as low SES), and students for whom at least one of the parents has more than 12 years of education and students (we classify them as high SES).

Table 2: Differences Between Choice Sets for High and Low SES Households - Pre Disclosure (2010-2012)

	All Choice Sets			Choices with Above Median Differences		
	Entire Sample	High SES	Low SES	Entire Sample	High SES	Low SES
	(1)	(2)	(3)	(4)	(5)	(6)
A. Average Difference (SDs) in the Choice Set Between the Best and Worst Option for:						
Test Scores	0.56	0.55	0.57	1.19	1.24	1.16
	(0.45)	(0.44)	(0.45)	(0.40)	(0.47)	(0.39)
Violence	0.96	0.94	1.01	2.29	2.14	2.39
	(0.90)	(0.81)	(0.97)	(0.84)	(0.88)	(0.83)
Satisfaction	0.93	0.86	0.97	2.02	1.84	2.08
	(0.75)	(0.65)	(0.80)	(0.51)	(0.43)	(0.50)
Value-Added	1.06	0.91	1.08	1.33	0.90	1.37
	(1.12)	(0.95)	(1.11)	(1.24)	(0.67)	(1.19)
B. Increased Probability of Attending a School with a 1 SD Increase in the Attribute - Pre Disclosure (Log Likelihood)						
Test Scores	0.015	-0.038	-0.023	-0.14***	0.079	-0.213***
	(0.013)	(0.029)	(0.017)	(0.032)	(0.075)	(0.043)
Violence	0.003	-0.018	-0.007	0.021	0.329***	-0.080*
	(0.014)	(0.031)	(0.018)	(0.026)	(0.070)	(0.031)
Satisfaction	0.114***	0.051	0.031	0.124***	0.454***	0.062
	(0.016)	(0.037)	(0.021)	(0.036)	(0.086)	(0.049)
Value-Added	0.022***	0.034***	-0.001	0.083***	0.080***	0.072***
	(0.004)	(0.010)	(0.006)	(0.010)	(0.029)	(0.014)
Number of Students	42,654	13,056	24,315	9,857	2,795	6,207

Notes: This table presents the pre disclosure average differences in the attributes among school options within each choice set (Panel A). It also shows the estimated increased log likelihood of attending a school with a 1 standard deviation higher value in the relevant school attributes in the pre disclosure years (Panel B). Columns (1)-(3) display results for the entire sample of choice sets, while columns (4)-(6) present results for the choice sets with above median disparities in the relevant attributes. Columns (2) and (5) present results for high SES households while columns (3) and (6) for the lower SES households. In Panel B, the results are estimated using the conditional logit model described in Equation (7) in the main text, where coefficients are estimated for the pre-treatment years. The Value-Added measures were calculated by estimation a middle school fixed effect in an education production function which includes standard school and student level inputs and for which the outcome variable was the end of high school student average matriculation score. School level controls include number of classes and number of students as well as a measure of the decile of the average social status of the student composition of the school. Student level controls include an indicator for male students, the number of siblings, an immigrant indicator, parental years of schooling, six ethnicity indicators, and lagged test score data from primary school. Above median differences for the Value-Added measure refer to above median differences in the Violence measure. I classify students as low SES if both parents have at most 12 years of schooling, while high SES students are defined as those with at least one parent having more than 12 years of education. Standard errors are computed using bootstrap and clustered at the choice set level. * indicates significant level at 10. **indicates significant level at 5. ***indicates significant level at 1 or lower. The number of observations is slightly smaller for the SES analysis as some students in our sample have missing data on parental education. The number of observations for the above median differences column refers to the violence attribute and varies depending on the attribute.

Table 3: The Effect of School Attribute Information on Parental Response - Conditional Logit

	Entire Sample	Above Median Differences
	(1)	(2)
A. General Effect		
Satisfaction*After	0.101***	0.469***
	(0.023)	(0.054)
Violence*After	0.034*	0.133***
	(0.020)	(0.038)
Test Scores*After	0.045**	0.061*
	(0.019)	(0.036)
B. Heterogeneity by School Differences		
Satisfaction*After*Above Median Differences	0.457***	-
	(0.060)	
Violence*After*Above Median Differences	0.076*	-
	(0.046)	
Test Scores*After*Above Median Differences	-0.026	-
	(0.033)	
C. Heterogeneity by SES		
Satisfaction*After*Low SES	0.138**	0.447***
	(0.059)	(0.145)
Violence*After*Low SES	0.053	0.233**
	(0.050)	(0.115)
Test Scores*After*Low SES	0.030	0.014
	(0.047)	(0.090)
D. Heterogeneity by Gender		
Satisfaction*After*Male	-0.019	-0.028
	(0.046)	(0.109)
Violence*After*Male	0.106***	0.169**
	(0.040)	(0.077)
Test Scores*After*Male	0.003	0.007
	(0.038)	(0.072)
E. Heterogeneity by Immigration Status		
Satisfaction*After*Native Born	0.328*	0.972*
	(0.180)	(0.509)
Violence*After*Native Born	0.110	0.475
	(0.150)	(0.326)
Test Scores*After*Native Born	0.283*	0.569
	(0.167)	(0.347)
Number of Students	84,987	19,643

Notes: This table presents estimates that compare changes in the weights parents assign to different school attributes following the disclosure of information. The reported results represent the change in the coefficients associated with the increased probability of selecting a middle school with a one-standard-deviation higher rating in a specific school attribute. These coefficients are log-odds ratios, which have been estimated using the conditional logit model detailed in Equation (7) of the main text. The pre-disclosure and post-disclosure years are stacked to `before' and `after' periods, respectively. Column (2) displays results for the sub sample of students where the difference in the relevant attribute between to `best' and `worst' schools in their choice set, based on this attribute, is above the median threshold. In Panel C, I classify students as low SES if both parents have at most 12 years of schooling, while high SES students are defined as those with at least one parent having more than 12 years of education. In panel E I classify native-born students as those from households where at least one parent was born in Israel. The number of observations for the above median differences column refers to the violence attribute and varies depending on the attribute. Standard errors are computed using bootstrap and clustered at the choice set level. * indicates significant level at 10. **indicates significant level at 5. ***indicates significant level at 1 or lower.

Table 4: Correlation of Attributes and Value-Added (VA) Measures

Measure	Violence	Satisfaction	Test Scores	VA	VA no Lagged Score Controls	VA with Choice Set FE
	(1)	(2)	(3)	(4)	(5)	(6)
Violence	1	-0.34	-0.14	-0.25	-0.19	-0.15
Satisfaction	-0.34	1	0.48	-0.06	0.46	0.04
Test Scores	-0.14	0.48	1	-0.05	0.6	0.04

Notes: This table presents the estimated correlations between the different school attributes and middle school value added measures. The value added measures were calculated by estimation a middle school fixed effect in an education production function which includes standard school and student level inputs and for which the outcome variable was the end of high school student average matriculation score. Column (4) presents the preferred value added measure which includes all student and school controls. School level controls include number of classes and number of students as well as a measure of the decile of the average social status of the student composition of the school. Student level controls include an indicator for male students, the number of siblings, an immigrant indicator, parental years of schooling, six ethnicity indicators, and lagged test score data from primary school. In Column (5) I estimate the value added without accounting for student ability, proxied by the primary school test scores. In Column (6) I add a choice set fixed effect, comparing middle schools from the same choice set. Further detail on the estimation is available in the main text.

Table 5: The Effect of School Attribute Information on Attending Higher Value Added Schools

	Entire Sample	Above Median Differences by		
		Violence	Satisfaction	Test Scores
	(1)	(2)	(3)	(4)
A. General Effect				
Value-Added*After	0.007	0.048***	-0.025*	-0.030*
	(0.005)	(0.008)	(0.013)	(0.011)
B. Heterogeneity by SES				
Value-Added*After	0.008	0.042**	0.093***	-0.027*
	(0.007)	(0.010)	(0.020)	(0.015)
Value-Added*After*High SES	-0.005	-0.045***	-0.088***	-0.008
	(0.012)	(0.022)	(0.031)	(0.024)
Number of Students	84,739	19,599	21,442	20,475

Notes: This table presents estimates that compare changes in the probability parents select a middle school with a higher value-added measure following the disclosure of information. The reported results represent the change in the coefficients associated with the increased probability of selecting a middle school with a one-standard-deviation higher value-added measure. These coefficients are log-odds ratios, which have been estimated using the conditional logit model similar to Equation (7) of the main text, where the measure of value-added replaces the school attributes in the equation. The value added measures were calculated by estimation a middle school fixed effect in an education production function which includes standard school and student level inputs and for which the outcome variable was the end of high school student average matriculation score. School level controls include number of classes and number of students as well as a measure of the decile of the average social status of the student composition of the school. Student level controls include an indicator for male students, the number of siblings, an immigrant indicator, parental years of schooling, six ethnicity indicators, and lagged test score data from primary school. The pre-disclosure and post-disclosure years are stacked to `before' and `after' periods, respectively. Column (2)-(4) display results for the sub sample of students where the difference in the relevant attribute between to `best' and `worst' schools in their choice set, based on this attribute, is above the median threshold. In Panel B, I classify students as low SES if both parents have at most 12 years of schooling, while high SES students are defined as those with at least one parent having more than 12 years of education. Standard errors are computed using bootstrap and clustered at the choice set level. * indicates significant level at 10. **indicates significant level at 5. ***indicates significant level at 1 or lower. The number of observations is slightly smaller for the SES analysis as some students in our sample have missing data on parental education.

Table 6: The Effect of Information Disclosure on Socio Economic Integration levels

	Gap Between the Groups (High-Low Education)					
	2010	2011	2012	2013	2014	2015
	(1)	(2)	(3)	(4)	(5)	(6)
A. In the Same Middle School						
% of peers from the high parental education group - choice group	21.2%	23.0%	24.2%	24.9%	25.6%	25.4%
% of peers from the high parental education group - non choice group	28.5%	28.2%	28.9%	30.2%	30.4%	29.1%
Change in the Difference in Differences	-	2.0%	2.7%	2.0%	2.5%	3.6%
	-	(1.1%)	(1.3%)	(1.3%)	(1.4%)	(1.5%)
B. In the Same Middle School - Adjusted for the Municipality Pool						
% of peers from the high parental education group - choice group	5.8%	5.5%	6.8%	6.2%	7.4%	7.9%
% of peers from the high parental education group - non choice group	10.5%	10.5%	10.1%	10.1%	10.8%	10.2%
Change in the Difference in Differences	-	-0.3%	1.0%	0.4%	1.6%	2.1%
	-	`(1.0%)	`(1.3%)	(1.2%)	(1.1%)	(1.4%)

Notes: This table displays year-by-year estimates of socioeconomic segregation in middle schools within our sample. For each column I calculate the gap between high and low SES students in the percent of school peers from the high parental education group (high SES group). I compare this gap for the sample of schools with student school choice to the sample without. I classify students as low SES if both parents have at most 12 years of schooling, while high SES students are defined as those with at least one parent having more than 12 years of education. In Panel B I implement the Hoxby and Turner (2019) adjustment, which divides the share of each education group in a school by the equivalent share in the city, to calculate the segregation measures after adjusting for the relevant pool.

Table 7: Correlation Between School Survey Factors and School Value-Added

Measure	Factor 1 - Perceived Teacher Performance	Factor 2 - Consistent School Presence	Factor 3 - Feeling Happy and Safe at School	Factor 4 - Strengh of Peer Relationships	Factor 5 - Unsafe Environment	Violence	Satisfaction	Test Scores	VA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Factor 1 - Perceived Teacher Performance	1	0.67	0.7	0.8	-0.74	-0.39	0.18	0.33	0.21
Factor 2 - Consistent School Presence	0.67	1	0.47	0.72	-0.61	-0.43	0.1	-0.02	0.41
Factor 3 - Feeling Happy and Safe at School	0.7	0.47	1	0.6	-0.67	-0.51	0.72	0.17	0.1
Factor 4 - Strengh of Peer Relationships	0.8	0.72	0.6	1	-0.74	-0.49	0.13	-0.18	0.24
Factor 5 - Unsafe Environment	-0.74	-0.61	-0.67	-0.74	1	0.33	-0.23	0.15	-0.29

Notes: This table presents the estimated correlations between the identified factors underlying the GEMS student surveys, the different school attributes and the estimated middle school value added measures. The value added measures were calculated by estimation a middle school fixed effect in an education production function which includes standard school and student level inputs and for which the outcome variable was the end of high school student average matriculation score. Column (9) presents the preferred value added measure which includes all student and school controls. School level controls include number of classes and number of students as well as a measure of the decile of the average social status of the student composition of the school. Student level controls include an indicator for male students, the number of siblings, an immigrant indicator, parental years of schooling, six ethnicity indicators, and lagged test score data from primary school. For further details on the estimation of value-added measures and factor analysis, please refer to the main text.

Table 8: The Network of Information Sharing - The Increase in Uniformity of School Choice of Similar Origin Students Post Disclosure

	Herfindahl-Hirschman Index (HHI)
	(1)
A. Soviet Born Parent Subsample	
Post Disclosure	323.0***
	(82.7)
B. Entire Sample	
Post Disclosure	57.08
	(51.9)
Post Disclosure*Soviet Born Parent	266.9***
	(84.2)

C. Effect of Information for Soviet Born Parents

	Share Attending #1 Option		
	Satisfaction	Violence	Test Scores
	(2)	(3)	(4)
Post Disclosure	-2.883	-0.328	-2.591
	(2.234)	(2.228)	(2.225)
Post Disclosure*Above Median HHI	6.842**	-0.855	1.608
	(3.183)	(3.173)	(3.170)
Number of Students	82,880	82,880	82,880
Number of Students with a Soviet Born Parent	11,310	11,310	11,310

Notes: This table presents evidence related to shifts in the uniformity of middle school choice for different groups of parents following the information disclosure. The shifts in the share of students choosing the same middle school options, between the pre disclosure to the post disclosure years, are estimated using the changes in the Herfindahl-Hirschman Index (HHI) concentration levels of the percentage of students from the same group within a primary school class attending each middle school in the choice set. The results estimating shifts in concentration in panel A are for the subsample of households in which at least one parents immigrated from a former soviet union country. Panel B compares the increased concentration levels for the groups of soviet born households in the same classroom in primary school to the increased concentration for the group containing the rest of the classroom. Panel C provides results for the sub sample of students with a Soviet born parent, comparing classes with above and below median shifts in HHI. The estimate compares, for each primary school class, the percentage increase in the share of students choosing the best-rated middle school option in their choice set in terms of satisfaction ratings (column 2), violence levels (column 3) and test scores (column 4), in the years following the information disclosure. For further details on the estimation, please refer to the main text. * indicates significant level at 10. **indicates significant level at 5. ***indicates significant level at 1 or lower.

Table 9: The Effect of The Size of the Information Network on Parental Response to School Attribute Information

	Entire Sample			Low Socio-Economic Status		
	Soviet Born	Native	Difference	Soviet Born	Native	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
A. Effect of Number of Soviet Peers						
Satisfaction*After*Above Median # of Soviet Peers	0.138	0.026	-0.111	0.230*	-0.029	-0.259*
	(0.091)	(0.054)	(0.105)	(0.127)	(0.065)	(0.143)
Violence*After*Above Median # of Soviet Peers	0.229***	0.085*	-0.143*	0.339***	0.149***	-0.191*
	(0.073)	(0.045)	(0.086)	(0.100)	(0.055)	(0.114)
Test Scores*After*Above Median # of Soviet Peers	-0.104	-0.042	0.062	-0.198	-0.057	0.140
	(0.078)	(0.048)	(0.092)	(0.110)	(0.058)	(0.125)
B. Effect of Number of Native Peers						
Satisfaction*After*Above Median # of Native Peers	0.118	0.091*	-0.027	0.087	0.163**	0.075
	(0.099)	(0.054)	(0.113)	(0.138)	(0.065)	(0.153)
Violence*After*Above Median # of Native Peers	0.112	0.029	-0.083	0.099	0.007	-0.092
	(0.080)	(0.044)	(0.092)	(0.111)	(0.053)	(0.123)
Test Scores*After*Above Median # of Native Peers	0.028	0.169***	0.141	0.111	0.215***	0.104
	(0.086)	(0.048)	(0.099)	(0.121)	(0.059)	(0.134)
Number of Students	11,310	71,570	82,880	5,949	41,491	47,440

Notes: This table presents the estimates of the effect of having a larger number of classroom peers from a specific ethnic group on the changes in the weights parents assign to different school attributes following the disclosure of information. These changes represent the change in the coefficients associated with the increased probability of selecting a middle school with a one-standard-deviation higher rating in a specific school attribute. These coefficients are log-odds ratios, estimated using the conditional logit model detailed in Equation (7) of the main text. The pre-disclosure and post-disclosure years are stacked into 'before' and 'after' periods, respectively. Columns (1) and (4) display results for the subsample of students for whom at least one parent has immigrated from a former Soviet-Union Country. Columns (2) and (5) display results for the subsample of students for whom both parents were born in Israel. Columns (3) and (6) present the differences between the responses of Soviet-born and native-born households. Columns (1)-(3) include the entire sample, while Columns (4)-(6) display results for the subsample of lower socio-economic status. I classify students as low SES if both parents have at most 12 years of schooling, while high SES students are defined as those with at least one parent having more than 12 years of education. Panel A displays the interaction of having an above-median number of Soviet peers in the classroom with the main effect (the changes in the weights parents assign to different school attributes following the disclosure of information). Panel B displays the interaction effect of having an above-median number of native peers in the classroom with the main effect. In all the regressions, we control for the total number of students in the classroom. Standard errors are computed using bootstrap and clustered at the choice set level. * indicates significance at the 10% level. ** indicates significance at the 5% level. *** indicates significance at the 1% level or lower.

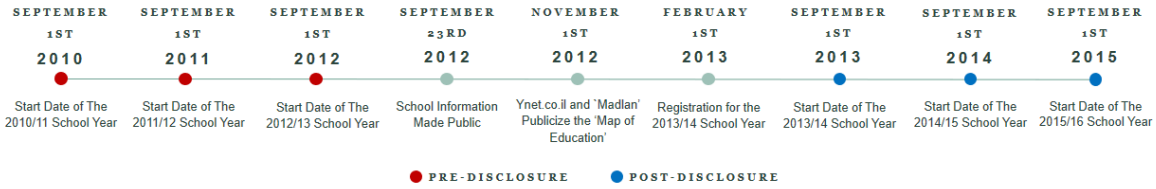


Figure 1: Timeline of the information release.

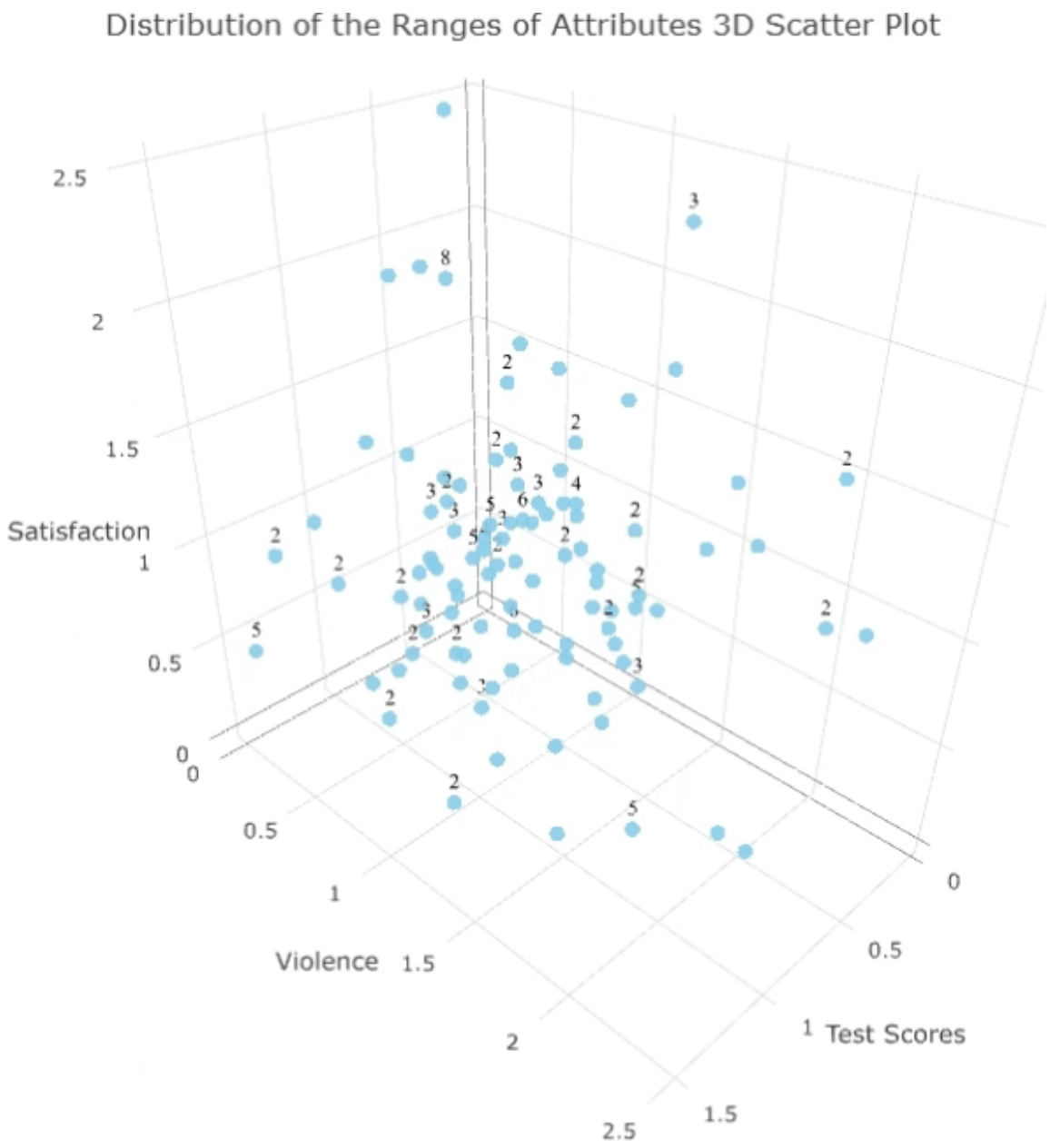


Figure 2: Distribution of the Ranges of Attributes in the Choice Set.

Note: This figure displays the joint distribution of ranges between the best and worst options for test scores, violence levels, and school satisfaction levels within each choice set. Numbers next to dots indicate multiple observations with identical values.

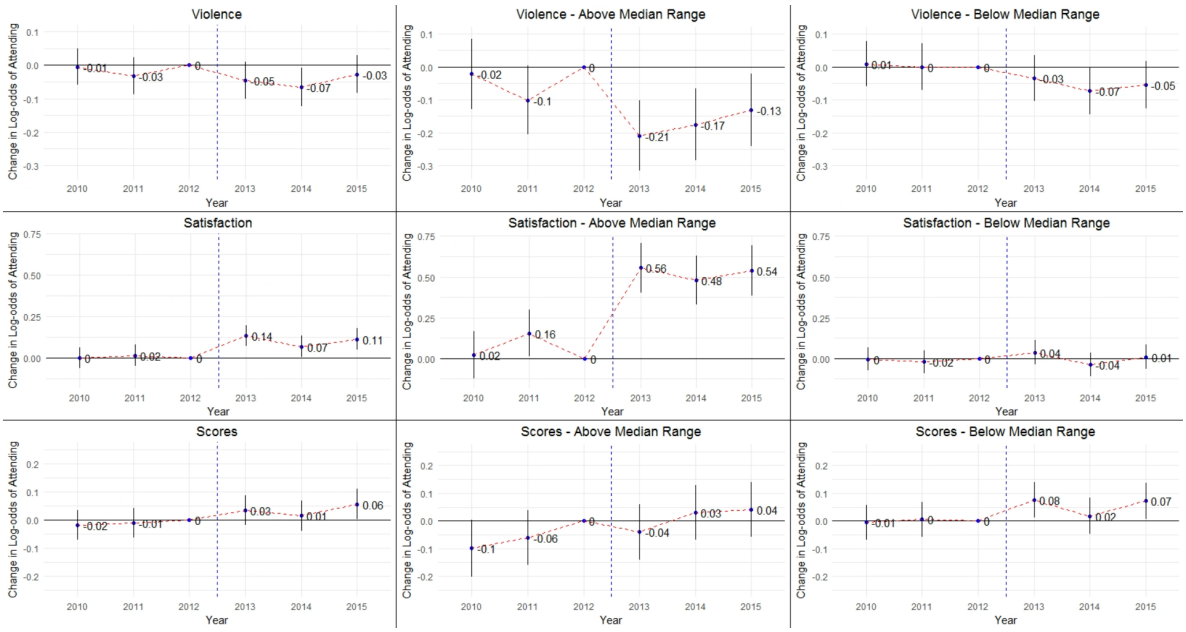


Figure 3: Parental Response to the Information Release.

Note: This figure presents estimates comparing changes in the weights assigned by parents to different school attributes following the disclosure of information. The reported results represent the change, relative to the baseline of 2012, in the coefficients associated with the increased probability of selecting a middle school with a one-standard-deviation higher rating in a specific school attribute. These coefficients are log-odds ratios, which have been estimated using the conditional logit model detailed in equation (6) of the main text. Results for the above (below) median range are for the sub sample of students for whom the difference in the relevant attribute between to 'best' and 'worst' schools in their choice set, based on this attribute, is above (below) the median threshold. Confidence intervals are the 95 percentile and are estimated using bootstrap and clustered at the choice set level.

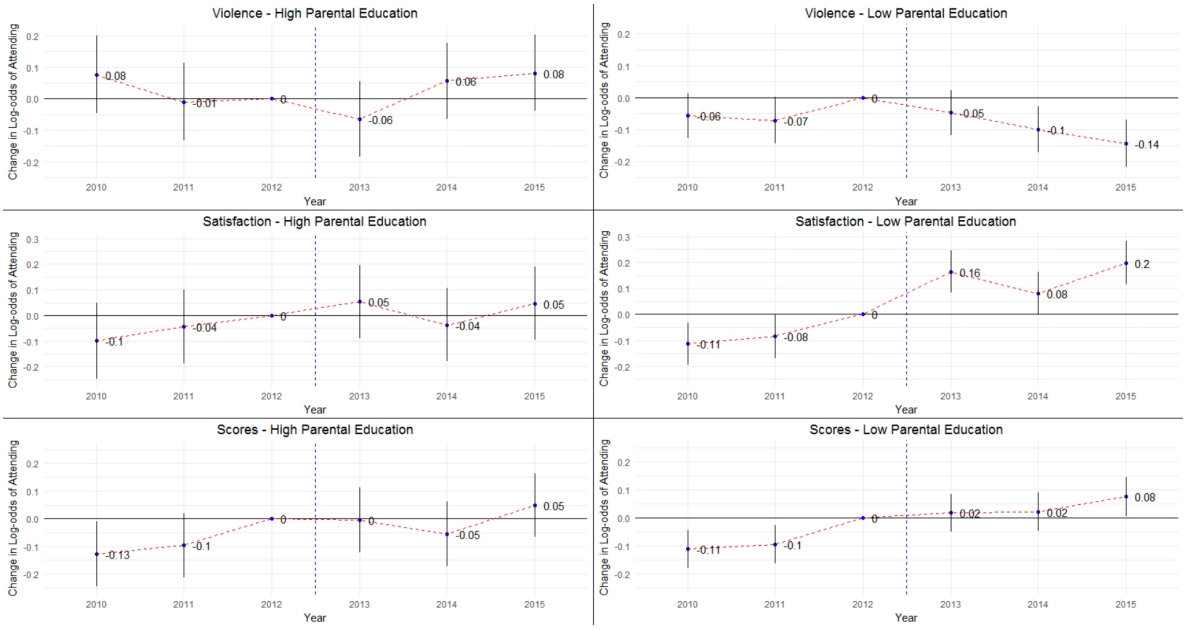


Figure 4: Heterogeneity by SES Levels of Parental Response to the Information Release.

Note: This figure reports estimates that compare changes in the weights parents assign to different school attributes following the disclosure of information. The reported results represent the change, relative to the baseline of 2012, in the coefficients associated with the increased probability of selecting a middle school with a one-standard-deviation higher rating in a specific school attribute. These coefficients are log-odds ratios, which have been estimated using the conditional logit model detailed in equation (6) of the main text. Results for the low parental education group are for the sub sample of students for whom both parents have at most 12 years of schooling, while the high education group consists of students with at least one parent having more than 12 years of education. Confidence intervals are the 95 percentile and are estimated using bootstrap and clustered at the choice set level.

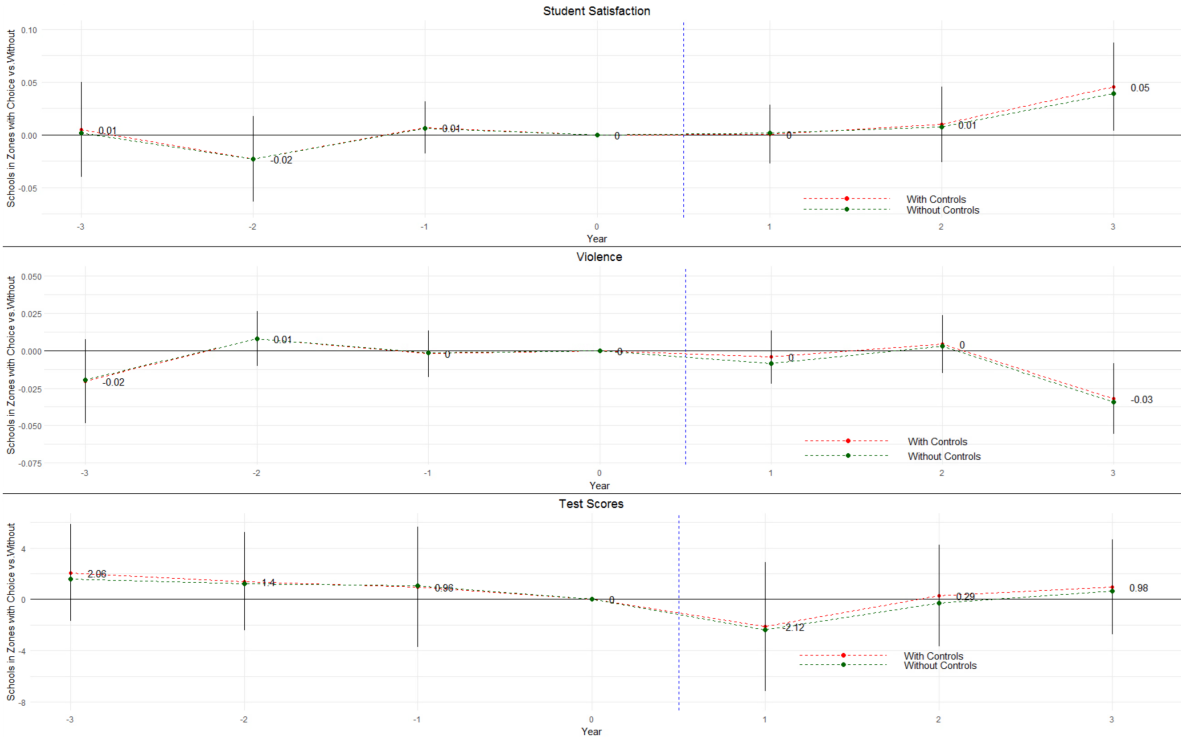


Figure 5: School Response.

Note: The figure shows estimates of k analogous to those defined in equation (9), where k is the number of years since the information disclosure. The coefficient k shows the residualized difference between schools in region with school choice and those without for the various school attributes. The dashed green line traces out estimates without controls for time varying school characteristics. Standard errors are clustered at the school level, and 95 percent confidence intervals are displayed.

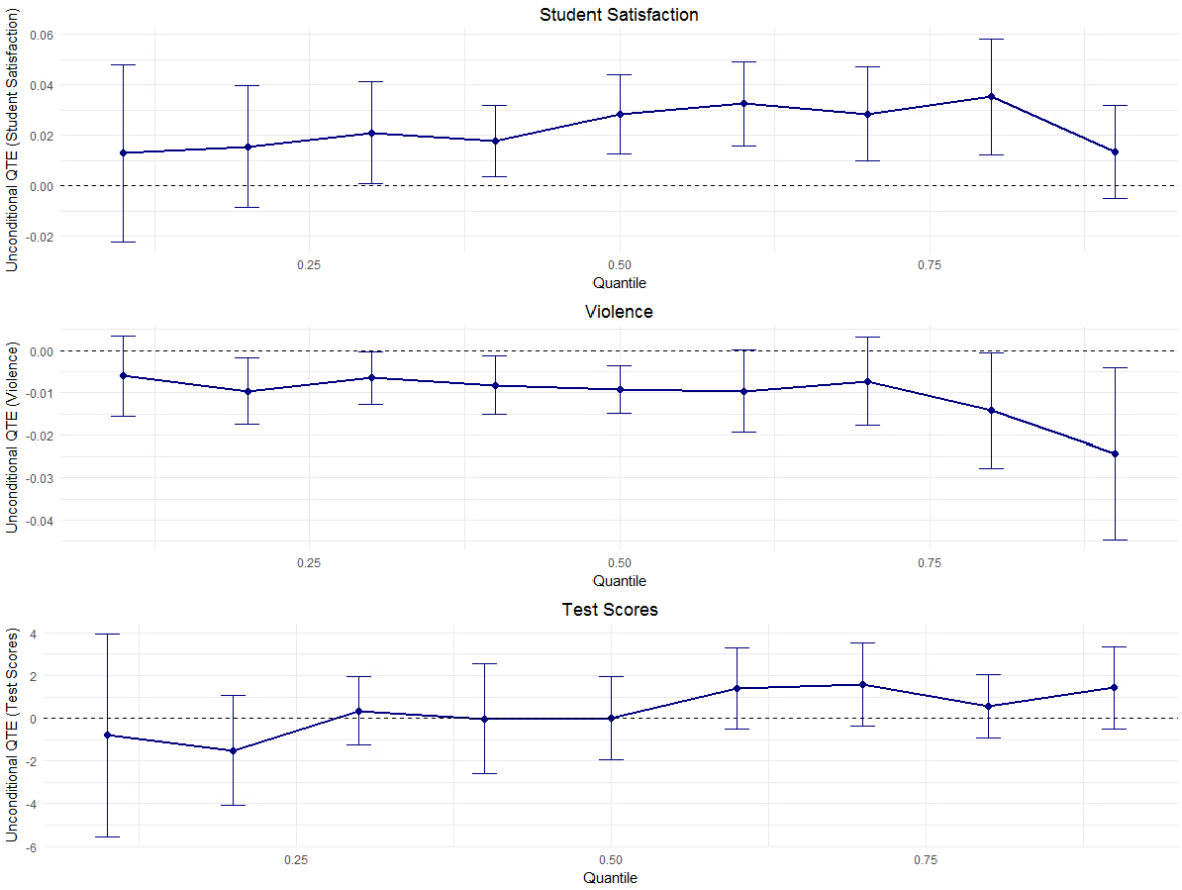


Figure 6: Quantile Treatment Effects on School attributes.

Note: This figure reports unconditional quantile treatment effects estimated by inverting both the observed average treatment effect distribution for the schools in regions with choice and the estimated counterfactual distribution in the final year of our sample. Bootstrapped standard errors are used to construct 95 percent confidence regions.

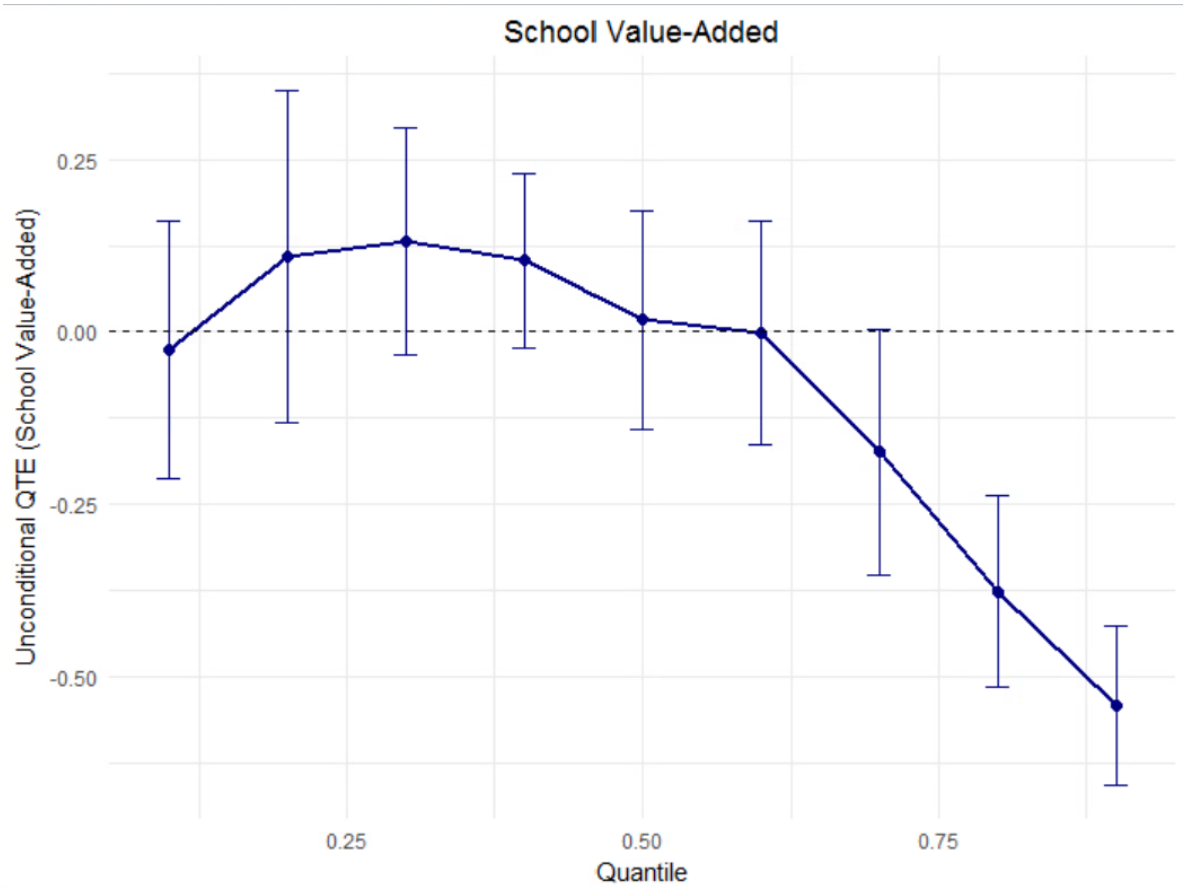


Figure 7: Value Added Quantile Treatment Effects.

Note: This figure reports unconditional quantile treatment effects of the school value added measures estimated by inverting both the observed average treatment effect distribution for the schools in regions with choice and the estimated counterfactual distribution in the final year of our sample. Bootstrapped standard errors are used to construct 95 percent confidence regions.

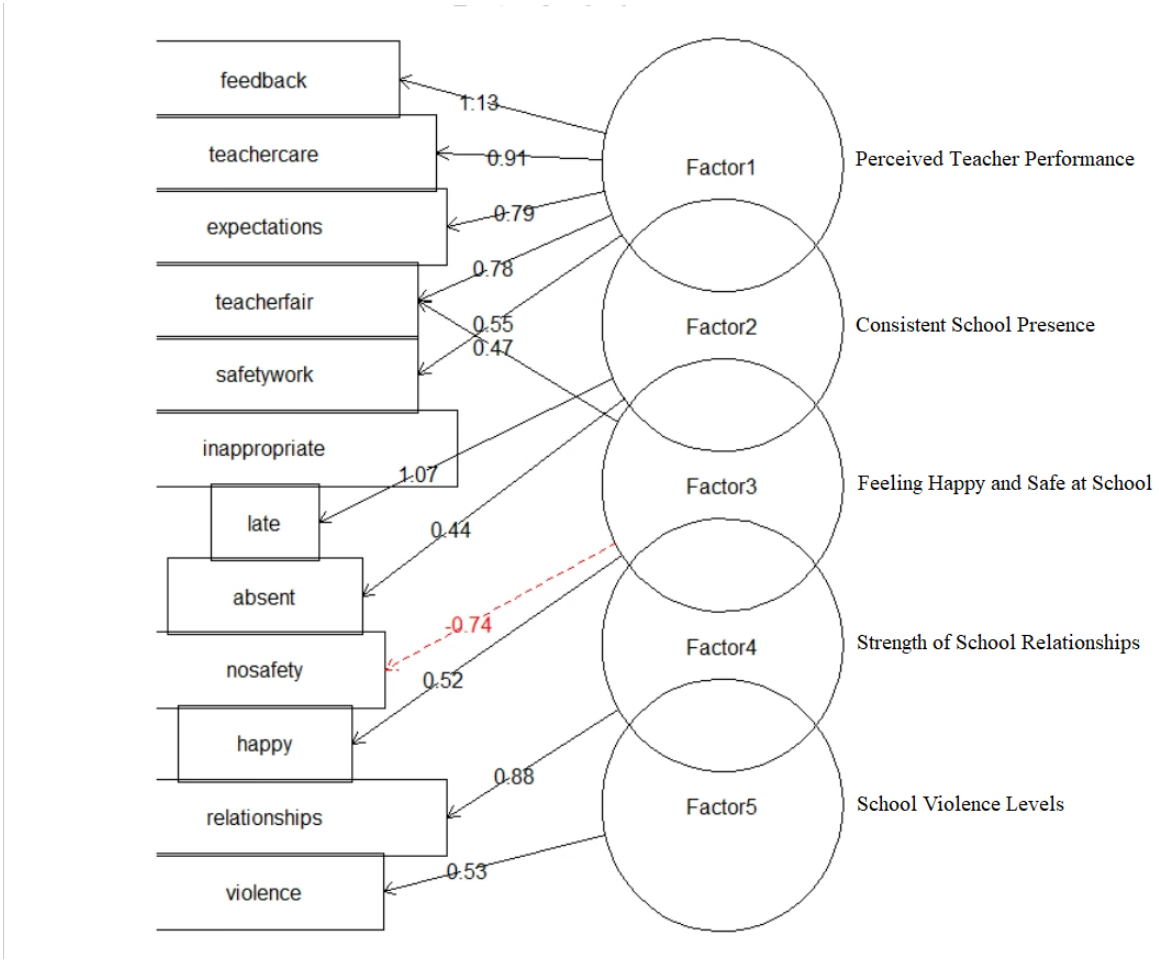


Figure 8: Factor Loading From Survey Questions to Underlying Concepts.

Note: This figure presents the factor loading of the groups of survey questions asked in the middle school GEMS student surveys evaluating different aspects of school life. Descriptions on the right of each factor are the author's interpretations of the constructs each factor captures.

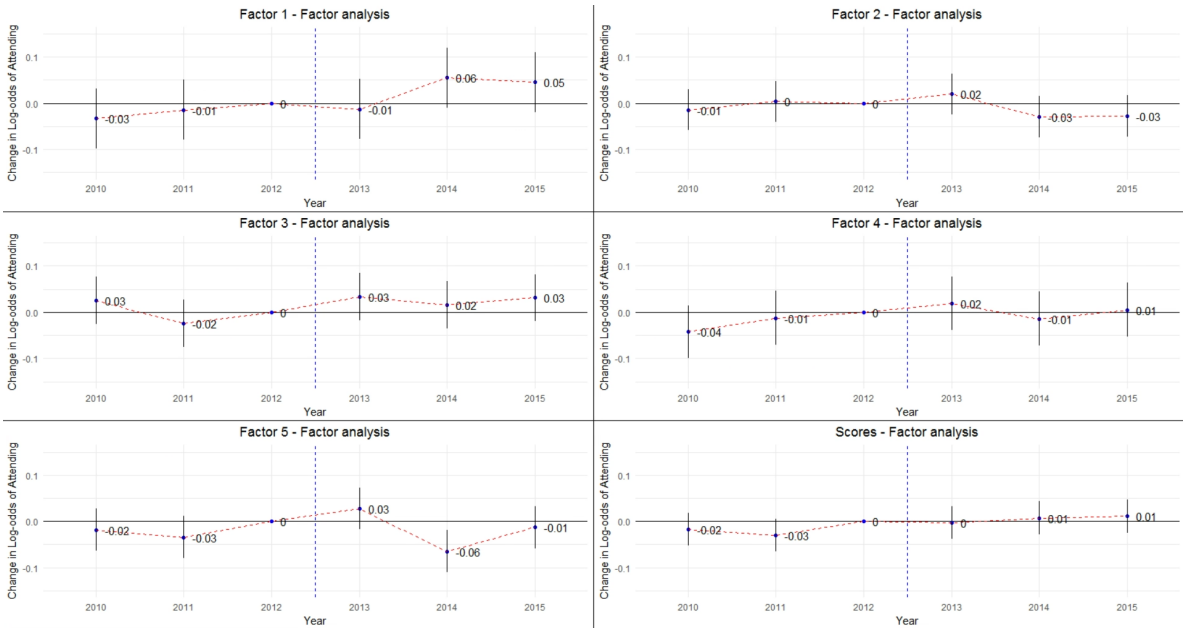


Figure 9: Parental Response to the Information on Attribute Factors for All Survey Question.

Note: This figure reports estimates that compare changes in the weights parents assign to the 5 latent factors from the student surveys describing different facets of school life, following the disclosure of information. The reported results represent the change, relative to the baseline of 2012, in the coefficients associated with the increased probability of selecting a middle school with a one-standard-deviation higher rating in a specific school attribute. These coefficients are log-odds ratios, which have been estimated using a variation of the conditional logit model detailed in equation (6) of the main text, in which the 5 latent factors from the student surveys are used instead of the publicized satisfaction and violence attributes. Confidence intervals are the 95 percentile and are estimated using bootstrap and clustered at the choice set level.

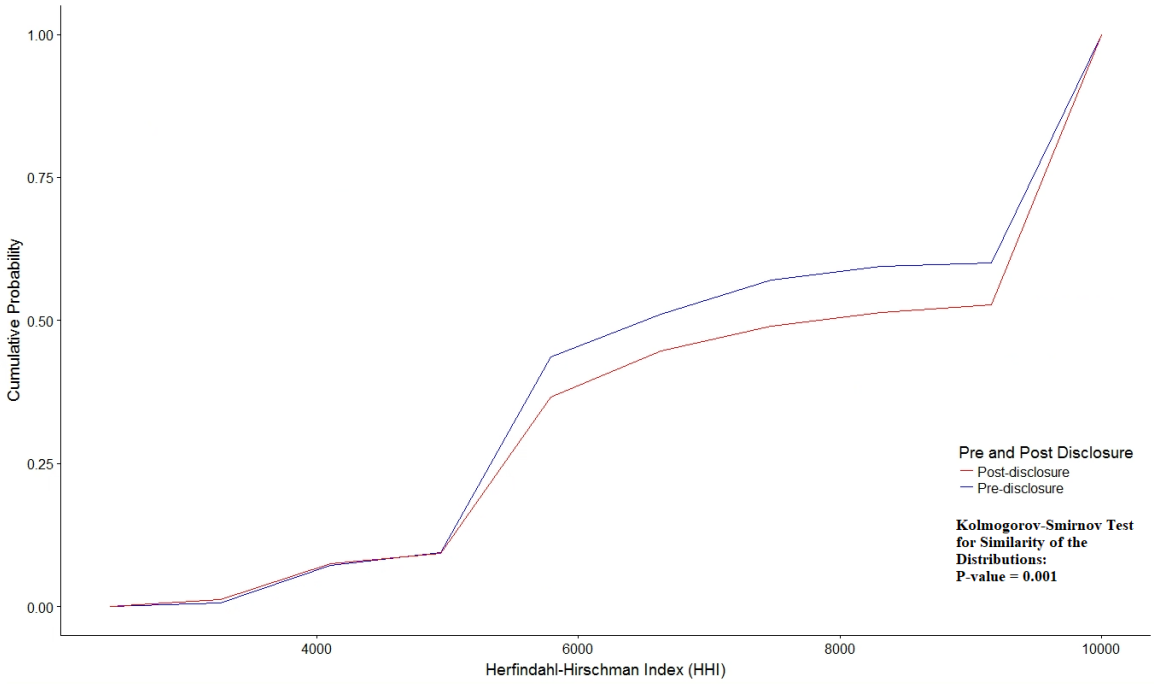


Figure 10: Cumulative Distribution of HHI for Each Primary School Class Pre and Post Disclosure - For Soviet Union Born Parents.

Note: This figure presents the cumulative distribution of HHI values for each primary school class pre and post information disclosure, for the subsample of households in which at least one parents immigrated from a former soviet union country.

A Appendix Tables and Figures

Table A1: Residual Variation for each School Attribute Within the Choice Set

Sample	Standardized test scores			Violence			Satisfaction		
	1(a)	1(b)	1(c)	2(a)	2(b)	2(c)	3(a)	3(b)	3(c)
	R2	σe	$\lvert e \rvert > 1/7$	R2	σe	$\lvert e \rvert > 1/7$	R2	σe	$\lvert e \rvert > 1/7$
Entire Choice Set	0.899	0.318	0.653	0.737	0.513	0.768	0.786	0.463	0.773
Above Median Differences	0.845	0.479	0.820	0.739	0.687	0.820	0.706	0.656	0.874
Below Median Differences	0.944	0.212	0.558	0.868	0.290	0.667	0.882	0.303	0.696
High SES	0.853	0.303	0.651	0.741	0.464	0.690	0.758	0.394	0.726
Low SES	0.889	0.320	0.663	0.727	0.545	0.802	0.765	0.486	0.775
High SES + Above Median Differences	0.730	0.483	0.850	0.772	0.628	0.754	0.773	0.527	0.797
Low SES + Above Median Differences	0.847	0.476	0.848	0.732	0.708	0.849	0.670	0.687	0.835

Notes: This table summarizes the residual variation left for each school attribute after regressing the attribute on choice set fixed effects and the other attributes. Each group of three columns shows (a) measures of R2 for the regression, (b) the standard deviation of the residuals (remaining attribute residuals), and (c) the fraction of middle school options with a residual larger than one-seventh of the standard deviation for each dependent variables.

Table A2: Robustness of The Effect of School Attribute Information on Parental Response

	Entire Sample	Above Median Differences
	(1)	(2)
A. Main Specification		
Satisfaction*After	0.101***	0.469***
	(0.023)	(0.054)
Violence*After	0.034*	0.133***
	(0.020)	(0.038)
Test Scores*After	0.045**	0.061*
	(0.019)	(0.036)
B. Linear Probability Model		
Satisfaction*After	0.077***	0.164***
	(0.017)	(0.021)
Violence*After	0.037***	0.064***
	(0.012)	(0.018)
Test Scores*After	0.009	0.019
	(0.017)	(0.029)
C. With An Additional Pre and Post Treatment Year		
Satisfaction*After	0.063***	0.487***
	(0.024)	(0.074)
Violence*After	0.011	0.086***
	(0.019)	(0.040)
Test Scores*After	0.032	0.033
	(0.021)	(0.041)
Number of Students	87,945	19,098

Notes: This table presents robustness tests for the estimates of the main conditional logit specification found in Panel A. Panel B reports results from a linear probability model with an estimation equivalent to the conditional logit model specified in equation (7) of the main text. Panel C presents results for a similar conditional logit model as the main specification, with the inclusion of an additional pre-treatment (2009) and post-treatment (2016) years to the sample. * indicates significant level at 10. **indicates significant level at 5. ***indicates significant level at 1 or lower. The number of observations specified pertains to the estimation related to Panel C. The number for the above median differences column refers to the violence attribute and varies depending on the attribute.

Table A3: Empirical Bayes Robustness of the Correlation of Attributes and School Value-Added Measures

Measure	Bayes Corrected VA	Bayes Corrected VA no Lagged Score Controls	Bayes Corrected VA with Choice Set FE
	(1)	(2)	(3)
Violence	-0.22	-0.29	-0.16
Satisfaction	-0.15	0.01	0.08
Test Scores	-0.18	0.06	0.03
Factor 1 - Perceived Teacher Performance	0.24	0.21	0.17
Factor 2 - Consistent School Presence	0.36	0.44	0.11
Factor 3 - Feeling Happy and Safe at School	0.04	0.16	0.2
Factor 4 - Strength of Peer Relationships	0.21	0.23	0.08
Factor 5 - Unsafe Environment	-0.26	-0.31	-0.08

Notes: This table presents a robustness to the estimated correlations between the identified factors underlying the GEMS student surveys, the different school attributes and the estimated middle school value added measures. I implement a Bayes shrinkage estimation strategy and construct an unbiased measure of middle school value-added that accounts for noise in the measurement when estimating the value added measure. Using this approach, the noisy measure of school value-added is multiplied by an estimate of its reliability. The reliability of a noisy measure is the ratio of signal variance to signal variance plus noise variance, see further detail in the main text. The value added measures were calculated by estimation a middle school fixed effect in an education production function which includes standard school and student level inputs and for which the outcome variable was the end of high school student average matriculation score. Column (1) presents the Bayes corrected preferred value added measure which includes all student and school controls. School level controls include number of classes and number of students as well as a measure of the decile of the average social status of the student composition of the school. Student level controls include an indicator for male students, the number of siblings, an immigrant indicator, parental years of schooling, six ethnicity indicators, and lagged test score data from primary school. For further details on the estimation of value-added measures and factor analysis, please refer to the main text.

Table A4: Empirical Bayes Robustness of the Effects of School Attribute Information on Attending Higher Value Added Schools

	Entire Sample	Above Median Differences by		
		Violence	Satisfaction	Test Scores
	(1)	(2)	(3)	(4)
A. General Effect				
Bayes Corrected Value-Added*After	0.004	0.047***	-0.052***	-0.038***
	(0.007)	(0.011)	(0.019)	(0.014)
B. Heterogeneity by SES				
Bayes Corrected Value-Added*After	0.006	0.040***	0.121***	-0.024
	(0.009)	(0.013)	(0.028)	(0.018)
Bayes Corrected Value-Added*After*High SES	0.004	-0.053***	-0.114***	-0.024
	(0.017)	(0.033)	(0.043)	(0.035)
Number of Students	84,739	19,599	21,442	20,475

Notes: This table presents the robustness estimates that compare changes in the probability parents select a middle school with a higher value-added measure following the disclosure of information. I implement a Bayes shrinkage estimation strategy and construct an unbiased measure of middle school value-added that accounts for noise in the measurement when estimating the value added measure. Using this approach, the noisy measure of school value-added is multiplied by an estimate of its reliability. The reliability of a noisy measure is the ratio of signal variance to signal variance plus noise variance, see further detail in the main text. The reported results represent the change in the coefficients associated with the increased probability of selecting a middle school with a one-standard-deviation higher value-added measure. These coefficients are log-odds ratios, which have been estimated using the conditional logit model similar to Equation (7) of the main text, where the measure of value-added replaces the school attributes in the equation. The value added measures were calculated by estimation a middle school fixed effect in an education production function which includes standard school and student level inputs and for which the outcome variable was the end of high school student average matriculation score. School level controls include number of classes and number of students as well as a measure of the decile of the average social status of the student composition of the school. Student level controls include an indicator for male students, the number of siblings, an immigrant indicator, parental years of schooling, six ethnicity indicators, and lagged test score data from primary school. The pre-disclosure and post-disclosure years are stacked to `before' and `after' periods, respectively. Column (2)-(4) display results for the sub sample of students where the difference in the relevant attribute between to `best' and `worst' schools in their choice set, based on this attribute, is above the median threshold. In Panel B, I classify students as low SES if both parents have at most 12 years of schooling, while high SES students are defined as those with at least one parent having more than 12 years of education. Standard errors are computed using bootstrap and clustered at the choice set level. * indicates significant level at 10. **indicates significant level at 5. ***indicates significant level at 1 or lower. The number of observations is slightly smaller for the SES analysis as some students in our sample have missing data on parental education.

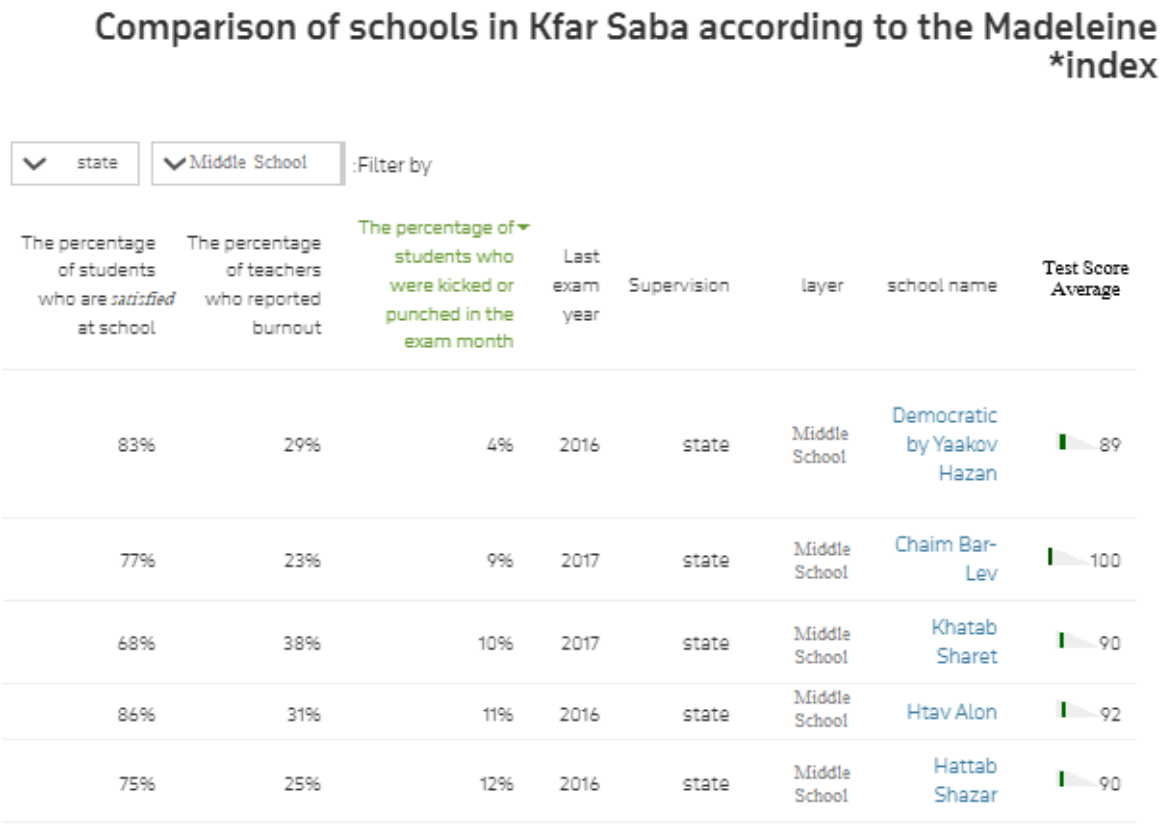


Figure A1: Translated Illustration of How *'The Israeli Education Map'* Project Presented Information for the Schools in each Municipality.

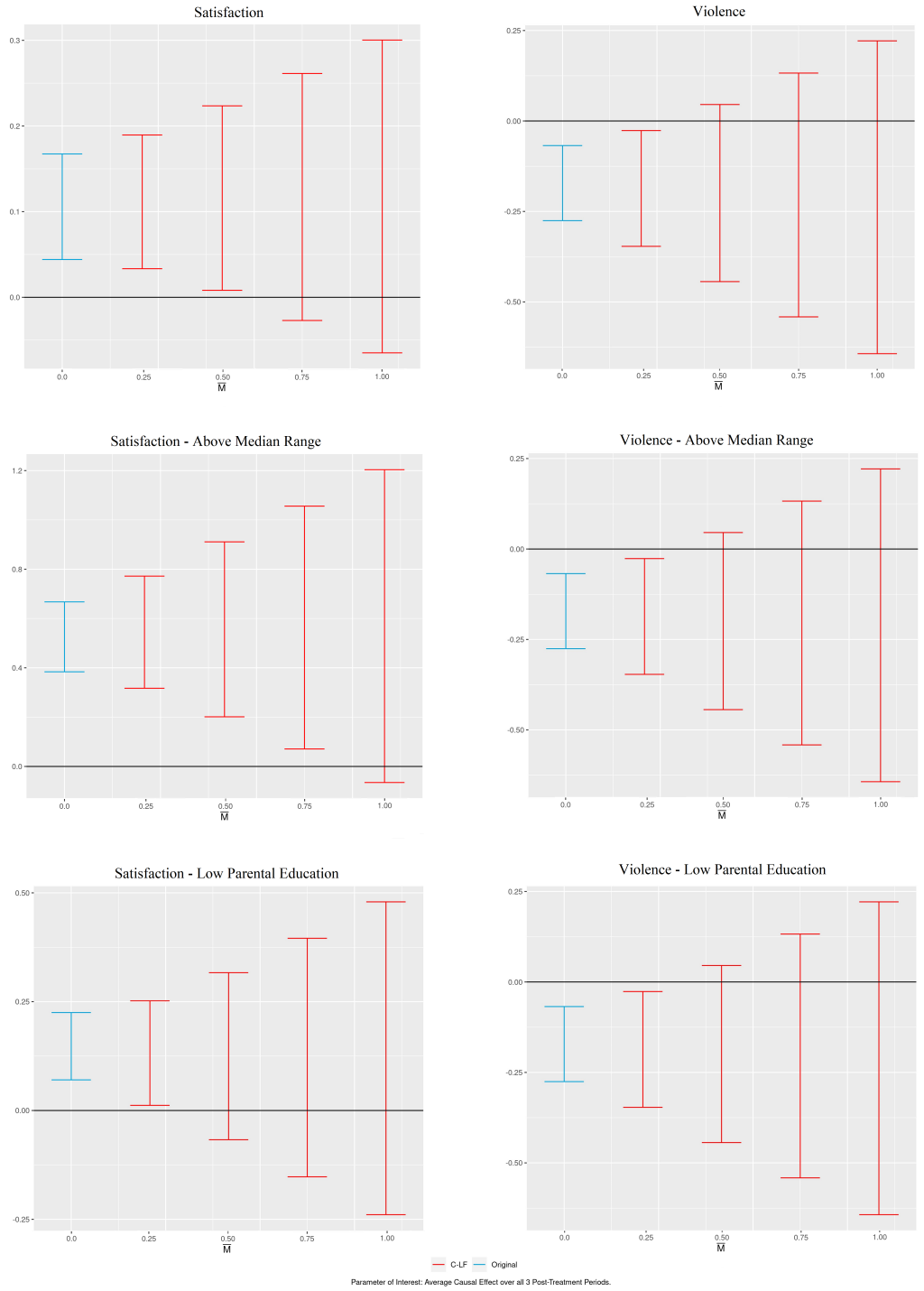


Figure A2: Pre-Trends Robustness - Bounding Relative Magnitudes of the Effect.

Note: This figure reports the confidence sets for the average parental response across all post-disclosure years, using the relative magnitude bounds proposed by Rambachan and Roth (2023). The results show calculations of the 95% robust confidence intervals for the average effect, constrained to be M times the maximum effect in the pre-disclosure period.

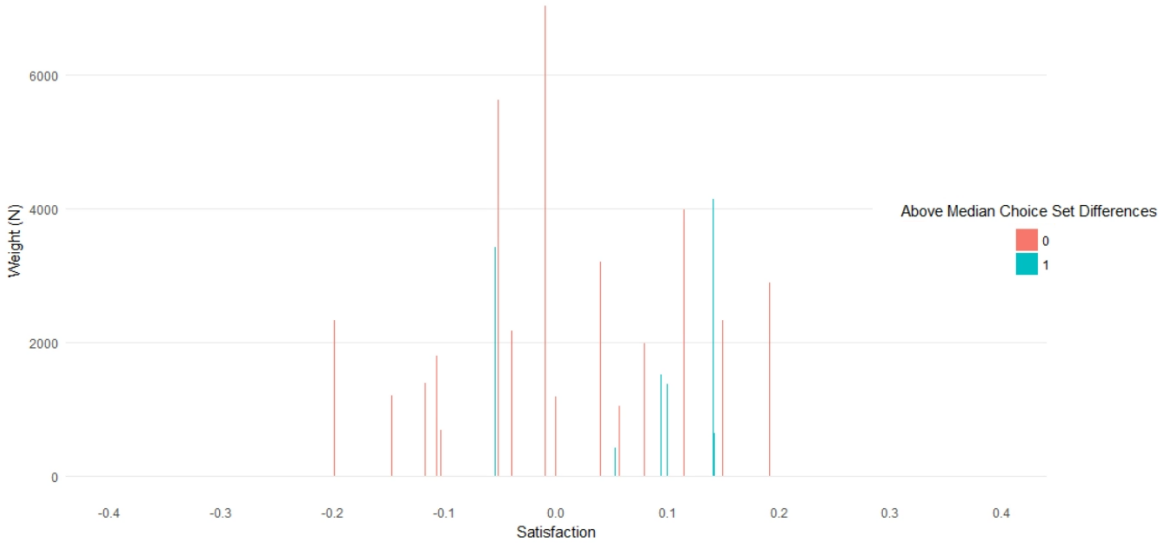


Figure A3: Distribution of Response to School Satisfaction Information by Municipality and by Choice Set Differences.

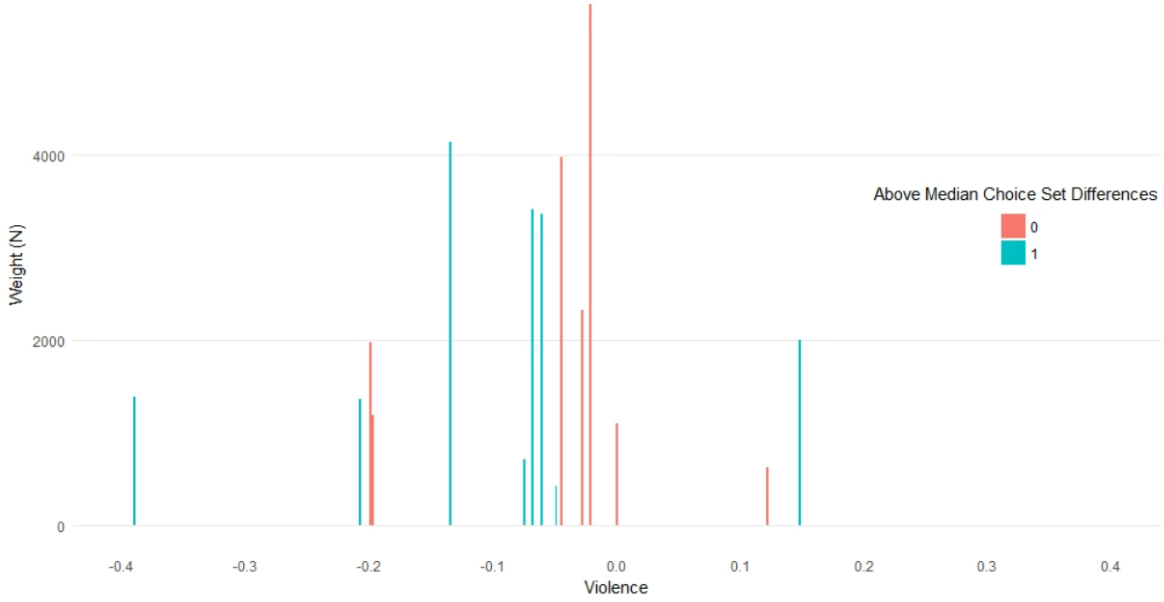


Figure A4: Distribution of Response to School Violence Information by Municipality and by Choice Set Differences.

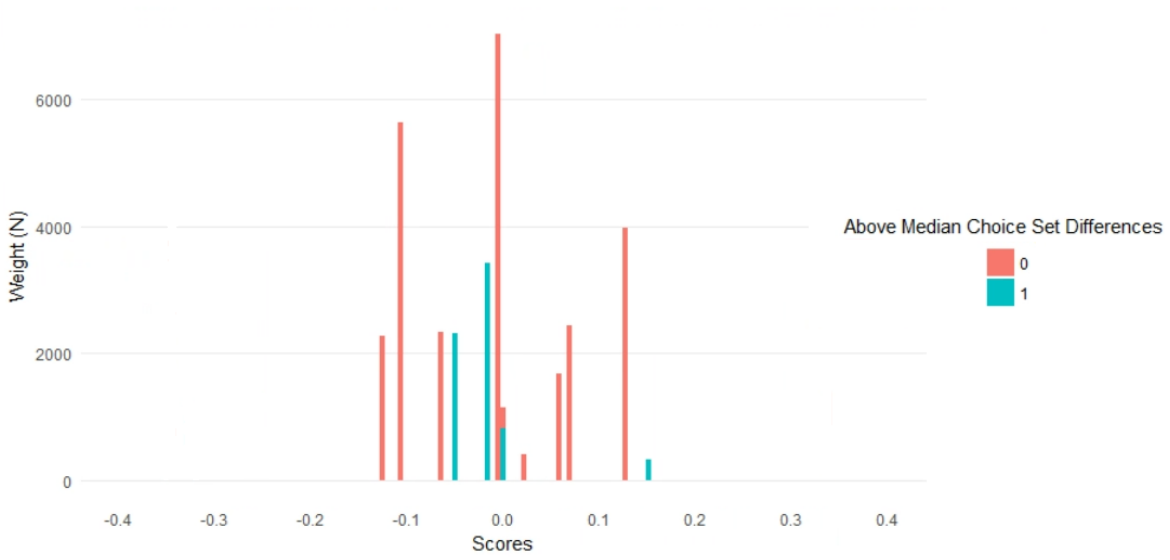


Figure A5: Distribution of Response to Test Scores Information by Municipality and by Choice Set Differences.

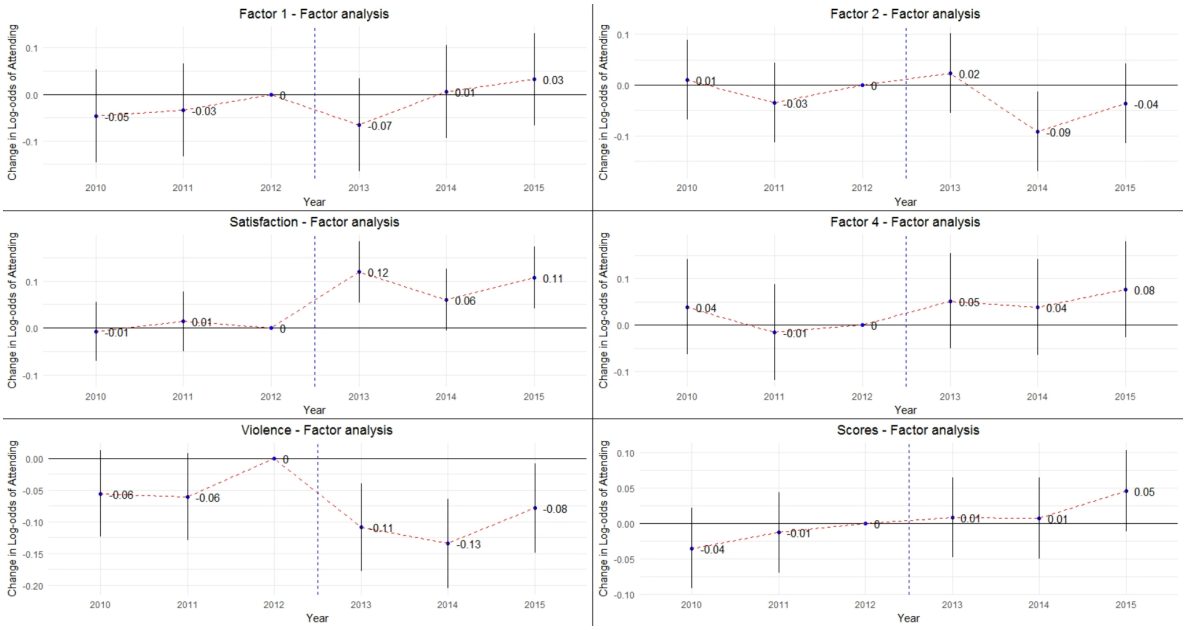


Figure A6: Parental Response to the Information the publicized attributes combined with Factors for Survey Question.

Note: This figure reports estimates that compare changes in the weights parents assign to publicized measures combined with the latent factors from the student surveys, following the disclosure of information. The reported results represent the change, relative to the baseline of 2012, in the coefficients associated with the increased probability of selecting a middle school with a one-standard-deviation higher rating in a specific school attribute. These coefficients are log-odds ratios, which have been estimated using a variation of the conditional logit model detailed in equation (8) of the main text, in which the latent factors from the student surveys are added to the publicized satisfaction, violence and test score attributes. Confidence intervals are the 95 percentile and are estimated using bootstrap and clustered at the choice set level.

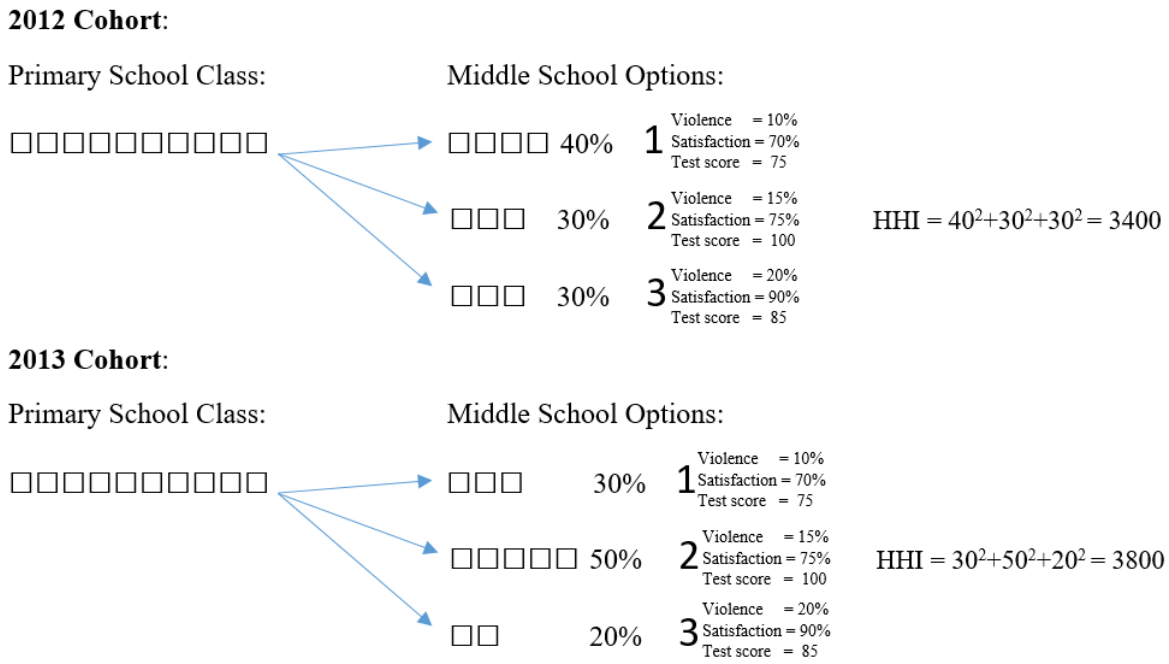


Figure A7: Illustration of the calculation of the HHI index for the concentration of groups into middle schools