Distorted Quality Signals: Evidence from School Markets

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Abstract

In markets where quality is imperfectly observed, disclosure policies are often implemented to inform consumers. The consequences of these policies are, however, unclear, specially in markets where quality is malleable. We study educational markets in Chile, where quality is signaled using test scores, and show that quality signals are distorted due to differences in student attendance the day of the test. The heterogeneity in distortions translate into misleading information used by parents when choosing schools. Using a demand model, we estimate how these distorted quality signals change school choices across poor and non-poor households. Although commuting costs and fees paid are unchanged in a counterfactual world with no distortions, chosen quality increases significantly. These results suggest that a low-cost information policy that eliminates distortions could increase welfare.

Keywords: schools, quality, disclosure, competition, choice

JEL Codes: I20, L15

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1 Introduction

In markets where quality is imperfectly observed, firms utilize prices and advertising to signal quality to consumers (Milgrom and Roberts, 1986). In the interest of consumers, regulators often implement disclosure policies, by which firms are required to provide certain information to the public. However, these policies create incentives that might induce undesirable behavioral responses by firms, such as reduced seller effort in detecting quality (i.e., gaming behavior), or trade-offs of effort across disclosed and undisclosed dimensions of quality (Dranove and Jin, 2010).

In this paper, we study the implications of mandated disclosure policies in educational markets. The school choice literature emphasizes that parents care about quality when choosing schools. In addition, in market-oriented systems, schools compete in order to attract more and better students. Therefore, schools benefit from signaling higher quality, particularly in a more competitive environment (Shleifer, 2004). Moreover, during the last decades governments have developed school accountability programs that utilize quality signals as measures of success. When quality signals are malleable, households could choose schools with distorted information about quality, potentially leading to inefficient choices.

We study the case of Chile, a market-oriented school system in which quality is signaled through a standardized test called SIMCE. This test is taken every year by all students (in specific grades) and is the focus of public debates about school quality. Using administrative datasets, we document that test scores at the school level are distorted due to changes in attendance the day of the test. Distortions arise because of non-random attrition of students across schools during test day. Although this type of behavior has been documented in other contexts—e.g. Dranove et al. (2003) shows how providers in the U.S. health system responded to a quality disclosure program by avoiding to serve sicker patients—less is known about its consequences. We take a step in this direction and study the causes and consequences of these distortions in quality signals.

Our analysis proceeds in three steps. First, we use administrative data on daily attendance at the student level to construct measures of distortions in quality signals induced by changes in students’ attendance. We document the existence of such distortions using an event study to show how the distribution of attending students changes on days in which SIMCE is taken. Then, drawing from the imputation literature in statistics, we propose a method by which we are able to recover undistorted quality signals and, therefore, the actual distortions behind the signals. We utilize these estimated distortions in quality signals for the rest of our analysis.
Second, we present a brief discussion of the theoretical mechanisms behind distortions and present correlations in our data. For instance, distortions may arise as a consequence of competition in the context of an oligopoly model. In addition, differences in the ability of schools to produce quality could explain part of the heterogeneity in distortions across schools. Third, given that we argue that quality signals are distorted through inducing changes in students' attendance, the cost of distortions should increase with class size. To guide our analysis, we present a signaling model for educational markets in Appendix A. In the model, schools optimally trade-off increasing observed quality through effective quality investments and through distorting observed signals, in order to maximize profits. There are, however, other mechanisms not considered in our model that may be driving distortions. We consider two cases: (1) performance prizes to school linked to test scores, and (2) informational channels that may have heterogeneous impacts across students.

In order to test for mechanisms empirically, we constructed a panel dataset of distortions at the school level for the entire educational system. Robust patterns appear in our analysis. First, schools of lower quality introduce higher distortions in their quality signals. Second, larger school introduce smaller distortions, which support the existence of a trade-off between generating quality signals through true quality or through distortions. Third, there is a negative relationship between competition and distortions for schools in small markets and no relationship in larger markets. In addition to these findings, we find a limited role of performance prizes and informational channels.

In the last part of our analysis, we estimate a school choice model to compute the impact of distorted quality signals on both school choices and households' welfare. This exercise measures the value the market places on having accurate (rather than distorted) information about quality. Our demand estimates are in line with previous findings in the literature and display significant heterogeneity across households’ types. We calculate that providing households with undistorted quality information would modify choices made by some households, that on average households would choose higher-quality schools, and that welfare implications are small on average but heterogeneous.

Our work is related to three strands of the literature. First, it is related to a number of papers from industrial organization that study the roles of disclosure and advertising in different markets. Regarding quality disclosure, Dranove and Jin (2010) provide a complete survey of the relevant literature and describe theoretical arguments by which mandatory disclosure may cause undesirable effects. Our paper focuses in a context of mandatory quality disclosure, which may encourage gaming by firms in order to disclose higher than effective quality. A relevant question that has been asked within this literature is whether quality disclosure effectively improves consumer choice. Evidence in this line shows that
most of the impacts operate on the margin of vertical sorting, which is that consumers switch towards higher quality products following increased disclosure. Work on analyzing the effects of quality disclosure in educational markets is somehow scarce and has yielded various results. For instance, Hastings and Weinstein (2008) report substantial impacts of providing households in Charlotte with report cards on the quality of chosen schools. Cooper et al. (2013) finds evidence in the same direction for households in different cities of Chile, although of a smaller magnitude. On the other hand, Mizala and Urquiola (2013) analyze household responses to a program that disclosed school quality in Chile—their intervention is certainly less powerful than the former in terms of the strength with which information was provided—finding no impacts from it.

Regarding advertising, Bagwell (2007) provides a thorough review of such literature. In our context, schools advertise their quality using test scores, which aid households’ search for schools. Thus, we focus on a case in which advertising is informative. Moreover, following the distinction proposed by Nelson (1970), the fact that schooling is an experience good implies that quality is hardly verifiable ex-ante, which implies that information acquired from advertising may be particularly important for consumers and therefore that distortions in quality signals may be relevant in this context. Our paper adds on the study of advertising choices by firms offering differentiated goods in oligopolistic environments, and focuses on educational markets, where few work has been done from an advertising perspective.

This paper is also related to a second literature that focuses on studying the perverse incentives of accountability systems in schooling markets, which have became increasingly frequent in the last decade. A number of papers have study how government programs that seek to place incentives to schools’ principals or teachers in order to address a given objective, end up causing unexpected adverse behavioral responses. Among this literature, Neal and Schanzenbach (2010) studies the case of accountability systems set by NCLB and provides evidence for the Chicago Public Schools for how teachers’ effort focus shifted across groups of students following changes in stringency of accountability, generally implying that low performance students received less attention; Figlio and Winicki (2005) studies the case of a performance accountability program in Virginia, to which schools reacted by increasing caloric intake of lunches during test days; Jacob and Levitt (2003) show how teachers responded by cheating in standardized tests to an incentive scheme implemented by the Chicago Public Schools; and Rouse et al. (2013) document changes in instructional practices by schools in Florida after being imposed accountability systems. Moreover, as discussed by Figlio and Loeb (2011), incentive programs designed on the basis of standardized tests are often subject to this kind of effects, which may certainly be related to the discussion proposed in Neal (2013) regarding the usage of test scores for multiple objectives. Our paper shows how manipulation of test scores from such tests can end up providing households with
inaccurate information for their school choices.

Finally, this paper is also related to the literature studying school choice in competitive markets, where papers such as those by Gallego and Hernando (2009) and Neilson (2014) for the chilean case, and Bayer et al. (2007), Hastings et al. (2009) and Walters (2014) for the case of the U.S., among many others, have focused on estimating households’ preferences over schools’ characteristics. These papers generally find that school fees, distance between the children home and school and school quality are the most relevant attributes of schools. However, the literature that focuses on understanding the role of information in school choice is still at an earlier phase, with Hastings and Weinstein (2008) and Cooper et al. (2013) being some papers in that line. To our knowledge, there is no paper measuring the value of information for school choice.

The remainder of the paper is organized as follows. In section 2, we describe the educational market in Chile, we present data sources, and estimate the effect of test day on attendance. In section 3, we construct measures of distortions in quality signals. In section 4, we explore a variety of explanations behind observed distortions at the school-year level. Finally, in section 5 we introduce a demand model and compute the welfare gains associated to a policy that eliminates distortions.

2 School Markets and Data

Our analysis focuses on the Chilean market for primary schooling. After a market-oriented reform was implemented in 1980, education has been served by a mixture of public and private (voucher and non-voucher) schools. Public schools are fully funded by the government, although occasionally charge parents with small fees. Private voucher schools are privately managed, although eligible for receiving public funding through vouchers. Private voucher schools are allowed to charge fees to parents in the form of copayments, although vouchers are phased out on the basis of those. Private non-voucher schools are privately managed and not eligible for receiving public funding. Over the last three decades, the private sector has steadily increased its market share.1

We use several administrative data sets from the Ministry of Education (MINEDUC). The first data set is an administrative record of schools operating in the market: type (public, private), enrollment, fees, participation in government programs and, importantly, their

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1Since 2005 the private sector has dominated the public sector. In 2013 public schools concentrated 37.5% of enrollment, while private voucher and non-voucher schools concentrated 53.5% and 7.5% of enrollment respectively (MINEDUC, 2013).
addresses, which will allows us to construct market-level measures. A second data set covers
the universe of students (approximately 3.5 million) and their basic demographics, daily atten-
tendance, and yearly performance at school. A third data set reveals students’ performance
in the SIMCE test of Math and Language, which we use to compute our measures of dis-
tortions to quality signals. These standardized tests are implemented yearly at the national
level for a subset of grades. We focus on 4th grade, as it is tested every year in our sample.
For each grade, the test day is the same across schools.2 Additional data sets include a
national school performance contest and the Chilean sociodemographic survey (CASEN),
which is matched with the municipality of each school to construct market level covariates
(e.g., household income).

2.1 Descriptive statistics

We construct two datasets: (1) a panel data set of schools observed every year between 2005–
2013, and (2) a panel data set of students observed daily in 2013. Although remarkably rich,
the student level data set has some limitations. First, daily attendance data is only available
for years 2011 and 2013. Second, attendance data is not available for non-voucher schools, as
they are not mandated to report attendance to the central government. Therefore, we only
consider public and voucher schools in our analysis, which represent 92.5% of enrollment in
2013. In addition, we remove from the dataset all schools with less than 10 students in order
to improve the precision of our measure of distortions introduced in section below.

The school level data set contains yearly information on schools offering 4th grade during
the period 2005–2013. The entry and exit of schools makes this panel unbalanced, but there
are 3,425 schools that operate every year. Panel A in Table 1 displays summary statistics
for these schools: 50% are public, 43% are voucher schools and 7% are private, and 11% are
located in rural areas. The average school serves approximately 32 students. More than half
of schools charge no fees, and the average annual fee is around $85,000 CLP (approximately
$140 USD). In terms of SIMCE test scores, schools in our sample are exactly at the national
average of 250. Finally, there is substantial potential competition across schools, with the
amounts of schools within short distances from other schools being somehow large: the
median school has as much as 40 schools at a distance smaller than 3km around it.

Panel B in Table 1 presents descriptive statistics for the student level data set. The first
variable (test score) was already discussed previously at the school level. For simplicity, we

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2For instance, test days in 2013 were October, 8th and 9th for 4th grade. Every year, students are tested
in both Language and Math. Note that, while the school performance data is available for all students in
the system, the data on test scores in the SIMCE tests is only available for students that attended on those
test days.
use the average of Math and Language test throughout the paper. The second variable at the student level is GPA, which goes from 1.0 to 7.0 in Chile, with a threshold of 4.0 to pass a class. The mean of this variable is 5.9. The last two variables are attendance rates in test day and non-test day. The former is simply the average of two indicator variables that take the value of one if a student went to school in test day—recall that there are two test days, so this variable takes the value of 0, 0.5, or 1 at the student level. The latter is the average attendance in the five non-test days previous to the test day and, therefore, takes the value of 0, 0.2, 0.4, 0.6, 0.8, and 1.

2.2 Quality signals and attendance on test day

School quality is signaled using the average test score of students: if average test score is relatively high, then parents infer relatively high quality. As the average test score of a school is the combination of students taking the test and their test scores, there are two ways for potential distortions to appear: (1) changing students’ test scores, or (2) changing students’ attendance. The former is, however, costly, because it requires substantial investment and returns are uncertain—in addition, supervisors are hired by the government to monitor students and teachers during test day in all schools. Therefore, we believe that the most likely source of distortion is attendance on test day.

There are some empirical requirements for attendance to distort quality signals. First, there needs to be meaningful heterogeneity in expected test scores within a school. Second, schools have to be able to identify which students are more likely to perform poorly on the test. Both requirements are met in our context: Panel A in Figure 1 shows a strong positive correlation between students’ GPA and test scores. This means that if GPA can empirically explain attendance on test day, quality signals will be distorted.

Before proceeding to our main analysis, we estimate the average treatment effect of test day on attendance rates. As we study attendance of students in the 4th grade, we use students in the 3rd grade as control group. Econometrically, we use an event study design at the day level. Let $I$ be the set of students taking the test (4th grade) and $J$ be those not taking the test (3rd grade). Then, we calculate:

$$
\beta_t = \frac{\sum_{i \in I} 1[a_{it} > 0]}{N_I} - \frac{\sum_{i \in J} 1[a_{it} > 0]}{N_J}
$$

where $t = \{-5, \ldots, 5\}$ indexes days, with $t = 0$ denoting test day, $a_{it}$ is an indicator for attendance of student $i$ in day $t$, and $N_I$ ($N_J$) is the total number of students in group $I$ ($J$). The terms on the right hand side of equation (1) are average attendance rates in day
among treatment and control students.

The lower panel in Figure 1 presents the empirical analogue of $\beta_t$. We also calculate $\beta_p^t$, the average treatment effect of test day on students in the $p$th percentile of the GPA distribution, with $p = 10, 25, 75, 90$. Vertical gray lines denote test days and we restrict attention to five days before and five days after the test. Average attendance increases by approximately 2 percentage points on test day, from 92% to 94% (black). This increase in attendance is concentrated among high-performing students (blue). Students with low GPA exhibit no increases in attendance rates (red). This means that students on the upper (lower) tail of such distribution are overrepresented (underrepresented) in the sample of test takers and, therefore, quality signals are distorted upwards. In the following section we show how differences in attendance on test day cause heterogeneous distortions in quality signals at the school level.

3 Measuring Distortions

We argue that a school’s quality signal is “undistorted” if all students took the test. Empirically, however, the existence of non-random heterogeneous absenteeism rates the day of the test distort quality signals. In this section, we describe our methodology to estimate the magnitude of these distortions at the school-year level.

3.1 Counterfactual signals

We consider a scenario with no absenteeism as ideal to calculate undistorted quality signals. Although daily attendance is only available for a couple of years, it is possible to identify absenteeism on test day at the student level using GPA and test scores data: students with GPA data but without test scores are absent on test day. The empirical challenge consists in estimating test scores for absent students. We use multiple imputation methods developed by Rubin (1987) to estimate test scores of absent students.

3.1.1 Multiple imputation methods

The basic idea behind multiple imputation methods is to generate many estimates for the missing data, using a common statistical framework, to account for the uncertainty associated

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3 As described by Rubin (1976), random absenteeism within a school would not lead to bias in quality signals. Absenteeism within a school is, however, far from random.
to imputation. There are essentially three steps in this process. First, we define the variable with missing data and the predictors. Let \( s_{ijt} \) be the test score of student \( i \) in school \( j \) and year \( t \), and \( x_{ijt} \) be a matrix of variables that predict test scores at the student level. These two sets of variables define the information to be used to generate estimates of unobserved test scores for absent students:

\[
s_{ijt} = f(x_{ijt}; \gamma_{jt})
\]

where \( \gamma_{jt} \) is a matrix of parameters to be estimated using the statistical model \( f(\cdot) \) in the sample of observed test scores. For simplicity we use a linear regression as statistical model, although results are robust to using other models. Importantly, the parameters \( \gamma_{jt} \) are estimated with uncertainty. This uncertainty can be taken into account in the imputations using draws from the asymptotic variance of the estimated parameters \( \hat{\gamma}_{jt} \).

In addition to the choice of a statistical model, we need to specify predictors of student test scores within schools \( x_{ijt} \). The chosen variables need to be strong predictors of test scores, both statistically and theoretically. In addition, these variables need to be available for all students in our dataset. Therefore, we chose a student’s average GPA at the end of the academic year and the following indicator variables: students who were in 4th grade the previous year, and students who studied at a different school the previous year. The latter variables capture a student’s context and academic history. This model can be used to predict test scores at the student level during the period 2005–2013.

### 3.1.2 Undistorted quality signals and uncertainty

After estimating test scores of absent students using a multiple imputation method, we can estimate the “undistorted” quality signal \( Y_{jt} \). This can be done by taking the average of test scores across students within schools every year. Multiple estimates of missing test scores imply that we estimate multiple average test scores for each school-year. Our estimate of an undistorted quality signal is the average of multiple averages. For further clarity, let \( \hat{Y}_{jt}^{(n)} \) be the average test score at school \( j \) in year \( t \) calculated using draw \( n = 1, \ldots, N \) from the asymptotic variance of the estimated parameters. Then, our estimate for the undistorted

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4Note that parameters are specific to a school-year. Hence, one might worry that the asymptotic variance is calculated poorly when using a small number students. In order to address this concern, we have repeated our analysis using a bootstrap procedure and results are similar.

5In additional exercises we replace average GPA by average GPA in Math and Language separately. Unfortunately, these variables are only available for the period 2011–2013.
quality signal is:

\[ \hat{Y}_{jt} = \frac{1}{N} \left( \hat{Y}_{jt}^{(1)} + \cdots + \hat{Y}_{jt}^{(N)} \right) \] (3)

Where \( N \) is the total number of draws. The uncertainty of our estimates, on the other hand, is reflected in the variance of \( \hat{Y}_{jt}^{(n)} \). Then, we proceed by ordering \( \hat{Y}_{jt}^{(n)} \) from lowest to highest within a school-year and take the percentiles 2.5 and 97.5 to generate bounds for our estimate \( \hat{Y}_{jt} \). This is analogous to the construction of a 95 percent confidence interval using a bootstrap procedure.

3.2 Distortions in quality signals

Let \( \psi_{jt} \) be the distortion in quality signals at school \( j \) in year \( t \), defined as the difference between observed \( (y_{jt}) \) and undistorted \( (Y_{jt}) \) quality signals. Because \( Y_{jt} \) is unobservable, we need to use our estimate from equation (3). Then, our estimates for distortions in quality signals are defined as:

\[ \hat{\psi}_{jt} \equiv y_{jt} - \hat{Y}_{jt} \] (4)

We generate bounds for these quantities using the bounds for \( \hat{Y}_{jt} \). This means that every school-year in our dataset has an estimated distortion, together with a lower and upper bound, thus acknowledging the uncertainty that involves estimating an unobserved parameter such as the arithmetic mean of test scores across all students within a school.

To increase precision, our analysis restricts attention to schools in which the statistical model in equation (2) uses more than 10 observations. More precisely, we study schools in which the difference between the number of students enrolled and the number of students taking the test is greater than 10. Schools dropped from our analysis have few students, are usually located in rural areas and (not surprisingly) their estimated distortions have extremely wide bounds. We are confident that this restriction does not diminish the external validity of our results, as our analysis includes 96 percent of enrolled students in 4th grade.\(^6\)

There are approximately 5,000 schools in our final dataset observed between 2005 and 2013. In addition, the average (standard deviation) school-year has 47 students (34), with 3.5 (4.3) students absent the day of the test.

Figure 2 presents estimated distortions for all school and years in our dataset. The y-axis represents distortions in test score points, while the x-axis orders schools from lowest

\(^6\)The total number of students in the full dataset is 2,203,707, a number that decreases to 2,114,347 when restricting attention to schools with more than 10 students taking the test.
to highest distortion. In order to acknowledge the uncertainty associated to the estimation of these distortions, we have also plotted the 95 percent confidence interval. In addition, we color distortions in gray if these are not statistically different from zero, and in green when these are different from zero. These graphs also display the percentage of distortions that are different from zero (24% every year). Some schools experience no absenteeism on test day and, therefore, their distortions are zero by definition.

Figure 3 presents the distribution of distortions. The average school in our dataset has a positive distortion of 2.7 test score points, approximately 0.1 standard deviations of observed test scores. The distribution of distortions has a standard deviation of 3.9 test score points and it is skewed towards the right. The facts that (1) the average distortion is different from zero, and (2) the distribution is far from normal, make clear that distortions in quality signals are not random variation in test scores. In the next section, we provide an empirical investigation of what drives these distortions.

4 Understanding Distortions

In this section, our interest is in understanding the heterogeneity we observe in distortions at the school level. We discuss theoretical explanations, and also present a variety of empirical evidence that rules out several potential mechanisms.

4.1 Theoretical explanations

The simplest way to explain the heterogeneity in distortions is through the lens of an advertising model. In this type of model, schools are profit-maximizing firms that incur in a cost to signal higher quality. Consumers in each market observe an imperfect measure of school quality:

\[ v_j = f(q_j, \psi_j, \epsilon_j) \]

where \( v_j \) is observed quality, \( q_j \) is effective quality, \( \psi_j \) is a distortion introduced by schools in order to signal higher quality, and \( \epsilon_j \) is a random error term that reflects the imperfect control that schools have over observed quality. Of course, increasing either \( q_j \) or \( \psi_j \) has a positive cost for schools.

There are many such models in the advertising literature. The most common prediction from this class of models is that schools of higher quality are more likely to increase \( \psi_j \) because their marginal return is higher (Nelson, 1974). However, this might not be the case
if low quality schools have lower costs for manipulating attendance or, analogously, if high quality schools have a lower cost of providing quality. This is an implication of a theoretical model we have been working on, which we present in Appendix A. Such model frames the problem as one in which schools compete in prices and observed quality in an oligopoly setting, where consumers are naive households choosing a school according to both their price and observed quality. Schools in the model can generate quality signals combining costly true quality with costly distortions to it. The main implication is the existence of a trade-off between signaling quality through true quality or through distortions. This trade-off can be driven by different sources of heterogeneity: differences in costs of providing true quality, differences in costs of implementing distortions to observed quality, and differences in households’ taste for quality.

There are, however, other potential theoretical explanations. For example, teachers might try to manipulate attendance on test day if their wages are linked to test scores. Or maybe informational treatments at the school (or market) level interact with other variables to create heterogeneity in distortions. Our setting allows us to rule out some of these alternative explanations. In what follows, we present empirical evidence that suggests these mechanisms are not relevant.

4.2 Explaining distortions empirically

We now provide four pieces of evidence to understand the observed heterogeneity in distortions. First, we exploit the panel nature of our data set to understand the role of school size and quality. Second, we test for the effects of competition using entry and exit of schools. Third, we study performance pay prizes to test for the role of teachers. And fourth, we use a quality disclosure policy implemented in 2010 to test for the role schools play in generating distortions.

4.2.1 School size and quality

In a model of school competition, schools face a trade-off between generating quality through true quality or a distortion. To understand this trade-off, we study the empirical relationship between distortions and school enrollment and true quality. Enrollment can be thought as a measure of the cost of distorting quality signals: the higher the number of students, the costlier it is to increase test scores by changing attendance. On the other hand, higher quality schools should implement less distortions.

We estimate the relationship between distortions and school size and quality using the
following regression:

\[ \psi_{jt} = f(X_{jt}) + \eta_j + \nu_t + \varepsilon_{jt} \] (5)

where \( X_{jt} \) stands for either enrollment or undistorted quality, \( \eta_j \) and \( \nu_t \) are school and year fixed effects, and \( \varepsilon_{jt} \) is a random error term. We estimate \( f \) non-parametrically using a local polynomial regression.

Results are presented in Figure 4, panels (a) and (b). Both results point in the expected direction: larger schools and higher quality schools have smaller distortions in quality signals, although the magnitudes of the effects are somehow small.

4.2.2 Competition

A competitive environment could change incentives to distort quality signals. We generate a school-year specific measure of competition calculating the number of schools operating within 3 kilometers. If competitive pressure pushes schools to signal higher quality in order to attract demand, then we would expect competition to have a positive effect on distortions. Conversely, if competition disciplines schools, we could expect competition to have a negative effect on distortions.

To test for the effect of competition, we estimate equation (5) using the number of competitors within 3 kilometers as independent variable, which we denote by \( N_{jt} \). Given the inclusion of school and year fixed effects, we are using within school variation over time. This means that we are using \( \Delta N_{jt} = \text{Entry}_{jt} - \text{Exit}_{jt} \) as variation. Grau et al. (2015) documents significant variation in this variable. Panel (c) in Figure 4 presents results. In small markets, an increase in competition is associated with smaller distortions in quality signals. However, this association disappears in larger markets.

4.2.3 Monetary incentives for teachers

An additional mechanism that could explain distortions are incentives placed by performance pay systems that reward teachers based on test scores. In the market we study, there is biannual performance pay contest called SNED which we can use to test for the role of teachers. SNED operates as follows: (i) groups of homogeneous schools are constructed; (ii) every two years, a multidimensional index is computed at the school level, which considers academic performance, improvement, and socioeconomic integration among other outcomes; (iii) schools are ranked within their groups according to the value of such index; and (iv) all teachers in schools covering the 25% – 35% of the total enrollment of each group get a
monetary prize equivalent to around 40% of a teacher’s wage.\textsuperscript{7} Important, SIMCE test scores account for 70% of the weight in the index calculation.

Given that (i) prizes are provided according to an index, and (ii) after each contest schools are informed of their outcomes, we can use a school’s index as a measure of incentives. We compute the distance of each school to the threshold for obtaining the prize. Schools closer to the threshold have more incentives to increase their test scores through distortions than those further away from the threshold either upwards (sure winners) or downwards (sure losers). Using this rationale, we estimate:

\[
\psi_{jt} = 1_{\text{IN}} f^{IN}(\text{SNED}_{jt-1}^{IN}) + 1_{\text{OUT}} f^{OUT}(\text{SNED}_{jt-1}^{OUT}) + \eta_j + \nu_t + \varepsilon_{jt} \quad (6)
\]

where \(\text{SNED}_{jt-1}^{IN}\) measures distance to the threshold for winners, and \(\text{SNED}_{jt-1}^{OUT}\) measures distance to threshold for losers, both in terms of index points. We use information from the previous contest to construct these variables. Our objects of interest are the functions \(f^{IN}\) and \(f^{OUT}\). If schools closer to the threshold have larger distortions, there is evidence of teachers manipulating attendance on test day.

Figure 5 presents six different plots for the relationship between distortions and schools’ distance to the threshold. We present results for the two years after the prize is awarded and both for raw distortions in quality signals and residualized distortions (net of school and year fixed effects, as well as school characteristics). Estimates of \(f^{IN}\) and \(f^{OUT}\) show, if anything, the opposite pattern: schools closer to the cutoff have lower or similar distortions to quality signals. These results suggest teachers are unlikely to be the source of distortions.

\subsection{4.2.4 Educational traffic lights}

Other quality disclosure policies could incentivize schools to introduce distortions in quality signals. In 2010, the Ministry of Education implemented a policy called “Educational Traffic Lights” (ETL) that we can use to test for this mechanism. The ETL policy consisted in sending information about 2009 SIMCE test scores to all households. This information included test scores and a classification of schools in “Red”, “Yellow” or “Green” categories, with clear cutoffs in test scores determining the category. Allende (2012) uses these discontinuities and finds that the policy affected school enrollment: households in red schools responded by enrolling in yellow schools, and households in yellow schools enrolled more in green schools. The ETL policy generated discontinuities in perceived school quality. Therefore, we expect schools closer to the cutoffs to have larger distortions.

\textsuperscript{7}Since 2006, the coverage of the prize was increased to 35% of the enrollment of the group. More details about this program can be found in Contreras and Rau (2012).
Figure 6 presents the linear relationships between test scores and distortions around the ETL policy cutoffs. Again, we present results for distortions and residualized distortions. These plots show that distortions increase around the cutoff between red and yellow schools. This means that schools introduce larger distortions in order to move towards the yellow category or avoid moving to the red category. This pattern, however, is not the same around the second cutoff. These results provide evidence that (some) low-quality schools generate distortions to signal higher quality.

4.2.5 Discussion

Several interesting patterns arise from the set of results previously presented. Larger and higher quality schools have smaller distortions, something suggested by our theoretical framework. However, the relationship between competition and distortions suggests a more complex set of incentives not captured by our model. On the other hand, our analysis of monetary incentives for teachers, and the ETL policy suggest teachers and schools are unlikely to be a source of distortions. In sum, we can rule out some mechanisms generating distortions, but more work is needed to improve our understanding of the observed heterogeneity in distortions in quality signals.

5 Implications of Distorted Quality Signals

In the final part of our analysis, we estimate a school choice model to evaluate the impacts of distorted quality signals. Using the estimated preferences of parents, we implement the counterfactual exercise of providing undistorted quality signals. This exercise allows us to compare observed with counterfactual outcomes, as well as to compute the welfare loss caused by distortions.

5.1 School choice model

We estimate a model of school choice in the lines of Bayer et al. (2007). When constructing the model, we impose certain assumptions. First, households are assumed to have full information both regarding the set of available schools and their characteristics. Second, note that this is a cross-sectional exercise, so we cannot include school and year fixed effects in this case, just school characteristics. If this assumption does not hold, our estimation would potentially yield attenuated elasticities. However, it is not in the scope of this paper to explore further in this direction.
we assume schools do not select students based on attributes and do not face capacity constraints, i.e., households can enroll their children in any school in their choice set. As discussed by Neilson (2014), these assumption is likely to hold in the Chilean school system. Finally, we assume the household’s location choice, and therefore its choice set in the school choice problem, is independent of the school choice problem. Although strong, this assumption is supported by the fact that there are no institutional constraints on the choice set based on the household’s residential location.

Let households be indexed by $i$ and schools by $j$. Households derive utility from schools’ price, quality and distance from their household, denoted respectively $p_j$, $q_j$ and $d_{ij}$. They also derive utility from other school characteristics $Q_j$. For notational simplicity, we denote $X_j = [p_j, q_j, Q_j]$, which includes $K$ attributes. Preferences are heterogeneous depending on households’ type, indexed by $r$. In our model, only observed heterogeneity in preferences is considered, as further explained below. Moreover, we allow for households to derive utility from schools’ unobserved characteristics $\xi_j$. Finally, each household has an idiosyncratic preference shock, $\varepsilon_{ij}$, which we assume is distributed T1EV.

Under these assumptions, household’s $i$ of type $r$ indirect utility from enrolling their children in school $j$ is:

$$u_{ij}^r = \sum_k x_{k,j} \beta_k^r + \xi_j^r + \beta_d^r d_{ij} + \varepsilon_{ij}$$  \hspace{1cm} (7)

where the first two terms measure utility from characteristics that depend only on the school and is therefore constant across households of type $r$ for a given school $j$, while the third term measures disutility from distance between household $i$ and school $j$ for households of type $r$, which varies across households. We can therefore rewrite equation (7) as follows:

$$u_{ij}^r = \delta_j^r + \beta_d^r d_{ij} + \varepsilon_{ij}$$  \hspace{1cm} (8)

such that the parameters of the model are contained in the vector $\beta^r$, but can be alternatively represented by the vector $\delta^r$ and by $\beta_d^r$. Note that $\delta_j^r$ is the component of utility derived from choosing school $j$ that is constant across individuals, the mean value of school $j$ for households of type $r$.

The probability of household $i$ choosing school $j$ can be derived analytically using households’ utility.$^{10}$ The choice probability of school $j$ by household $i$ of type $r$ predicted by the

$^{10}$In school choice models there is no obvious outside option. Therefore, we follow Neilson (2014) and instead normalize $\delta_1 = 0$ within each market.
model is a function of schools’ and households characteristics:

\[ p_{ij}^r(d, \delta, \beta_d) = \frac{\exp(\delta_j^r + \beta_d^r d_{ij})}{\sum_{l \in J_i} \exp(\delta_l^r + \beta_d^r d_{il})} \]  

(9)

where \( J_i \) is the set of schools in the market where household \( i \) is located. We use this result in the next subsections for both estimation of the model and for computing the counterfactual exercise of interest.

5.1.1 Estimation

We estimate the parameters of the model using a two step procedure. First, we estimate standard conditional logit models for each group \( r \) in the data. Second, we exploit the assumed linear functional form of the utility function of households in order to estimate the relationship between the preference parameters and school-level characteristics.

The first stage of the estimation procedure consists of estimating equation (9), which can be done by maximum likelihood. In order to allow for heterogeneity in preferences, this procedure is implemented within each of multiple cells defined on the basis of \( R \) socio-economic levels, \( T \) time periods and \( M \) markets. The former is determined by the eligibility of a student for a national program called Subvencíon Escolar Preferencial (SEP), which is determined fundamentally by participation in social programs that aim at supporting the poor. Therefore, we estimate \( R \times T \times M \) conditional logit models in the first stage, which yields the same number of vectors of preference parameters for \( \delta \) and \( \beta_d \).

The second stage exploits the assumed linear functional form of the utility function in order to estimate the following linear regression:

\[ \delta_{jmt}^r = \gamma_{0,m}^r + \sum_k x_{k,jmt} \gamma_k^r + \epsilon_{jmt}^r \]  

(10)

where \( \gamma_{0,m}^r \) is a constant specific to each market and household type; \( \gamma_k^r \) measures the effect of \( x_k \) on school mean value for households of type \( r \); and \( \epsilon_{jmt}^r \) is a mean-zero error term. Note that \( \gamma_{0,m}^r + \epsilon_{jmt}^r \) is equivalent to the unobserved school characteristic \( \xi_{jmt}^r \) in the model above.

A concern with this regression is the potential endogeneity of school characteristics, in particular of prices and quality. Therefore, we estimate this regression using an instrumental variables approach. We use two sets of instruments. First, for each school, we include as instruments the non-price and non-quality characteristics of other schools in the market, in lines with instruments suggested in Berry et al. (1995). Second, we also use teachers’ wages at
the market level, which arguably operates as a cost shifter for schools, such that it may affect their choices of prices, but not their unobserved attributes. Finally, we utilize temperature data at the market level on the day in which the quality signal was generated (i.e. the days in which the SIMCE test was taken) as an instrument for quality, which is motivated by a literature that studies the relationship between climate and academic achievement, as discussed in Graff Zivin et al. (2015).\footnote{We construct this variable using data from the Berkeley Earth dataset, which provides population-weighted estimates of daily temperature at the county level.}

We estimate the model using data for years 2013 and 2014, the only years in which students’ location data is available. In addition, we only utilize data for students in 1st grade in order to focus on the margin in which most school choices are made. In terms of covariates to be included in the vector $X_j$, we include school fees, quality as measured by average SIMCE test score of the school across Math and Language, whether the school has a religious orientation or not, and the share of poor students that attended the school in the previous year, as measured by the their eligibility to SEP.\footnote{We use data on monthly copayment faced by households as a measure of school fees. Moreover, we use data on whether students’ eligibility for SEP in order to adjust school fees accordingly: eligible students do not pay any school fees in schools that operate under the SEP regime.} Finally, we are able to compute the distance between households and schools using georeferenced data on their locations.\footnote{We compute the Euclidean distance between every household and school in each market. We then proceed to clean these results by (i) removing mass points, which arise from imperfect georeference; and (ii) removing students located further than 55 kilometers from the median location in the market.}

5.1.2 Market definition and estimating dataset

Defining markets in contexts of spatial competition is difficult. This, because determining which suppliers belong to the choice set of consumers is not straightforward. In contrast to the case of many school systems, in Chile there are no institutional constraints that limit the extent to which students can travel. Therefore, we need to choose a market definition.

We adopt an approach based on the spatial distance between schools. We chose this criteria given that distance has been shown to be a relevant determinant of school choice by previous studies in the literature. In our data, students average distance to chosen schools is of 2.05 kilometers (1.27 miles) and the 90th percentile of such distribution is 4.83 kilometers (3 miles). Therefore, it is sensible to argue that schools located far enough from each other may belong to different educational markets. We define an educational market as a cluster of schools in a closed polygon with no other school closer than 5 kilometers (3.11 miles) from its boundaries. Operationally, a market is uniquely identified from the adjacency matrix
of schools, where links are defined as two schools being closer than 5 kilometers from each other. In implementing this procedure, and therefore in estimation as well, we only consider schools located in urban areas. For estimation we only include markets with at least 20 schools and for which we have available data for at least 300 students. The map presented in Figure 7 provides an example from the resulting market definitions for the ten largest markets in the central valley of Chile, where 56% of the country’s population lives. Each dot is a school in our data set and markets are assigned different colors.\

A description of the resulting sample is displayed by Table 2. The number of households types is \( R = 2 \), the number of markets included in the sample is \( M = 22 \), and the number of periods covered is \( T = 2 \). Therefore, the estimating dataset is comprised by 88 cells. In average, 32.2% (28.9%) of the students attending schools in each market in 2013 (2014) are included in the sample, and 94.3% (91.8%) of the schools operating in each market are so respectively in each year. Moreover, an average of 52.3% (52.3%) students included in the sample across markets are eligible for SEP respectively in each year.\

5.1.3 Results

Given that the most relevant dimension of households’ types is socioeconomic levels, we present all the results by poor and non-poor households separately. Figure 8 displays the resulting estimates from the conditional logit models of the first stage of the estimation procedure. Panels (a) and (b) display the resulting coefficients in each market for distance between households and schools. In all these cases, the coefficient is negative, which reflects a decreasing utility for households from choosing a school further away from home. Interestingly, poor households show to be in average 12.8% more sensitive than non-poor households. Panels (c) and (d) present estimates of \( \delta_{jmt} \).

Table 3 present results for different specifications of linear regressions of the estimates of \( \delta_{jmt} \) on different sets of school characteristics and fixed effects. In this version of the paper, we only present results from OLS regressions. Columns 1 through 4 displays results for poor households, while columns 6 through 9 do so for non-poor households. Overall, results point in the expected direction: households’ utility is decreasing in the price charged by schools and increasing in their quality. Adding other characteristics, as the religious orientation of

\[ \text{As a robustness exercise, we estimated the model using counties as markets. For estimation, we included counties for which a large share of students resided in the market (at least 90%) and were we had available data for more than 300 students. Our estimates were quantitatively similar.} \]

\[ \text{We tested for differences in observables across students included and excluded of the sample, within each market. While some of the differences across groups are statistically significant, these are not economically significant and do not show a clear pattern.} \]
the school or the share of poor students does not modify results, nor does including market and year fixed effects.

There are interesting patterns of heterogeneity across poor and non-poor households. For instance, our preferred specifications in columns 4 and 9 imply that poor households are 155.3% more price-sensitive than non-poor households. Inversely, poor households are estimated to be 61.2% less quality-sensitive than non-poor households. This heterogeneity suggests that policies regarding quality disclosure will have heterogeneous effects across these demographic groups. These patterns of heterogeneity coincide with previous findings within the school choice literature (Gallego and Hernando 2009; Hastings et al. 2009; Neilson 2014).

This estimation procedure allows for a preliminary test for households’ sophistication in the context of distortions to quality signals. This test consists in including the distortion as an additional covariate. If households are sophisticated, then we should find that they correct quality signals from schools downwards (upwards) when distortions to those signals are positive (negative). Results in columns 5 and 10 suggest that a share of households are sophisticated. There is again heterogeneity across households types, with non-poor households being 148% more sophisticated than poor households.

### 5.2 Welfare gains from undistorted quality signals

In order to compute the effects of distorted quality signals on choices and welfare, we define two scenarios: baseline and counterfactual. The former corresponds to the environment in real life. The latter scenario corresponds to a counterfactual world in which households are provided with undistorted information about school quality. This exercise rules out changes in other variables (e.g., schools fees and school investments) as well as the existence of capacity constraints.

In the following results, we utilize our estimates \((\delta^*, \beta^*_{r})\) and the observed vector of schools’ characteristics \(X_j\) to compute choice probabilities and consumer welfare for the baseline scenario. For the case of the counterfactual scenario, calculations additionally use estimates of \(\beta^*_k\) from the second stage of the demand model, and a counterfactual vector of school characteristics \(\tilde{X}_{ij} = [p_{ij}, \tilde{q}_{ij}, Q_j]\), where \(\tilde{q}_{ij}\) stands for undistorted quality of school \(j\).\(^{16}\)

First, we need to construct a counterfactual vector of school quality. It is important to note that given that distortions are mostly positive, correcting has not only a relative effect across schools, but also an absolute effect at the market level, by which aggregate

\(^{16}\)More precisely, we utilize the results for the second stage from our preferred specifications: columns 4 and 9 of Table 3.
quality offered in the market decreases. In order to focus on the former, we construct the counterfactual quality by scaling the distribution of undistorted school quality at the market level such that its mean and standard deviation are equal to those of the distribution of observed school quality at the market level.

5.2.1 Households’ choices

We begin the analysis by examining schools’ choice probabilities by households across both scenarios. We do so by adjusting the choice probabilities predicted by equation (9) of our demand model and using the estimates from such model and the data on school attributes for both scenarios. Following equation (9), choice probabilities are therefore computed as $p_{ijmt}(d, \hat{\delta}, \hat{\beta})$ and $p_{ijmt}(\bar{d}, \hat{\delta}, \hat{\beta})$, where $\delta_{jmt} = \sum_k \hat{x}_{k,jmt} \hat{\beta}_k + \xi_{jmt}$ is the mean utility of school $j$ in market $m$ in period $t$, computed using demand estimates and data on counterfactual school quality.

Figure 9 displays the computed changes in choice probabilities between both scenarios. It is interesting to note that, despite the fact that the magnitude of the distortions is moderate, there is significant heterogeneity. This pattern holds when restricting the analysis to the set of schools actually chosen by parents, as displayed by Panels (c) and (d). This shows that changes in the quality disclosure system would induce changes in choices by households. However, given that households have a limited number of schools in their choice sets, these changes in choice probabilities may only induce actual changes in choices for a small fraction of households. Marginal changes in the observed vector of schools’ quality may not be enough to modify observed rankings. Note that the non-poor households display more variation in the computed changes, which is driven by their higher quality-sensitivity.

We now compute the predicted attributes of schools chosen by households under both scenarios. More precisely, we compute predicted attribute $k$ of schools chosen by households as the following weighted averages:

$$\hat{x}_{ik} = \sum_{j,m,t} p_{ijmt}(d, \hat{\delta}, \hat{\beta}) x_{k,jmt}$$

$$\tilde{x}_{ik} = \sum_{j,m,t} p_{ijmt}(\bar{d}, \hat{\delta}, \hat{\beta}) x_{k,jmt}$$

where weights are the choice probabilities already discussed above.

Figure 10 displays the distributions of attributes of predicted choices by households. Separate plots are presented for poor and non-poor households. Additionally, Table 4 displays the means of predicted attributes for each subpopulation. From Panels (a) and (b) in Figure
10, it is easy to note that changes are small and they do not change the mean. Similarly, Panels (c) and (d) in Figure 10 show only slight changes in the distributions of predicted fees paid by poor and non-poor students. Although mean changes in distance and prices across scenarios are minimal, there is a fair amount of variation across households.17

The variable that changes the most by this policy is the quality of schools chosen by parents. Panels (e) and (f) in Figure 10 present results. We observe a clear shift in the distribution towards higher quality levels. Poor households choose schools with 2.69% (0.29 s.d.) higher quality, while non-poor households would choose schools with 2.93% (0.32 s.d.) higher quality. In addition, there is substantial variation: as much as 4% (8%) of poor (non-poor) households would choose schools with lower predicted true quality in the counterfactual scenario, which is plausibly driven by the fact that choosing schools further away from home, or schools that charge higher prices, is costly.

5.2.2 Households’ welfare

Finally, we calculate the welfare changes of providing undistorted quality signals. In the baseline scenario households choose schools using the observed measure of school quality which, as discussed, is distorted. However, the effective utility of consumers is determined by undistorted school quality.18 This is not the case in the counterfactual scenario, in which households choices and utility depend on true school quality. This setting does not allow for measuring the change in consumer welfare using traditional methods in the literature (Small and Rosen, 1981; Petrin, 2002).

We address this challenge using a simulation approach. For each household, we draw preference shocks from a T1EV distribution, $\varepsilon_{ij}^{(s)}$. Using those draws, we compute choices for the baseline and counterfactual scenarios for each household as follows:

$$f_{i}^{(s)} = \arg \max_{j} \{u_{ij}^{(s)}\}$$

$$\tilde{f}_{i}^{(s)} = \arg \max_{j} \{\tilde{u}_{ij}^{(s)}\}$$

Then, denoting by $\tilde{u}_{ij}^{(s)}$ and $\tilde{u}_{ij}^{(s)}$ the utility levels obtained from the baseline and counterfactual choices, we compute the utility gain from moving from the baseline to the counterfactual scenario as $\Delta u_{i}^{(s)} = \tilde{u}_{ij}^{(s)} - \tilde{u}_{ij}^{(s)}$. In order to integrate over the distribution of preference shocks,

\[17\] The standard deviation of changes in predicted distance between schools and households (school fees paid by households) is equal to 0.031 (0.033) standard deviations of the variable in the sample.

\[18\] This distinction is similar to that utilized in the field of behavioral economics between choice utility and consumption utility.
we repeat this procedure $S$ times and then compute the average utility gain across replications. Moreover, we are able to translate these gains to monetary units by dividing by $\hat{\beta}_p r$, as usual in this literature. Therefore, we compute welfare gains for household $i$ as:

$$\hat{\Delta} C_S r_i = \frac{1}{S} \sum_{s=1}^{S} \frac{1}{\hat{\beta}_p} \Delta u_i^{(s)}$$

which we can then aggregate across households types and markets in order to compute the welfare loss for the educational market. This aggregate welfare change measures the value placed by consumers for having access to undistorted information about the quality of services provided by schools.

The results from these calculations are presented in Panel (a) of Figure 11, which displays estimated changes of consumer welfare from moving from the baseline to the counterfactual scenario, for $S = 1,000$ draws. The results show that for all households, welfare would increase in the counterfactual scenario. For poor households, the average welfare gain we estimate is of $17$ CLP ($0.034$ USD). Moreover, 66% of the households in that group display welfare gains. Regarding non-poor households, they display larger variance in these results. Their average welfare gain we estimate is of $165.3$ CLP ($0.33$ USD), and 87% of the households in that group display welfare gains. Scaling up this results for the complete educational system, welfare gains would add up to $228,923,630$ CLP ($457,847$ USD) yearly.

These results suggest small gains from providing undistorted information. This is the case because the gains computed correspond to the average across simulations. However, as argued before, the policy of interest would only marginally affect the vector of perceived school quality. Therefore, given that the supply of schools faced by households is limited, we would only expect a small share of households to actually react to the policy by switching to a different school. In our simulations, that share was equal to 0.85% (1.67%) for poor (non-poor) households. We compute welfare changes for that marginal population of switchers as follows:

$$\hat{\Delta} C_{S r_i, \text{switchers}} = \frac{1}{S S_i} \sum_{s=1}^{S} \frac{1}{\hat{\beta}_p} \Delta u_i^{(s)} 1\{j_i^{s(s)} \neq \tilde{j}_i^{s(s)}\}$$

where $S_i$ is the number of simulations for which household $i$ chooses a different school in the baseline and counterfactual scenarios. Panel (b) in Figure 11 displays results for the distribution of welfare gains of households conditional on switching. For this subpopulation gains are larger. The average welfare gain for switchers is of $1,919.6$ CLP ($3.83$ USD) for poor households and of $9,363$ CLP ($18.72$ USD) for non-poor households.
The fact that non-poor households benefit more than poor households from the information policy is evident, and the magnitudes of the differences, striking. There are two explanations for these differences. First, as our preferences’ estimates show, the former are more quality-sensitive than the latter and, therefore, will be more willing to take advantage of relative changes in perceived quality of schools in their market. Second, our preferences’ estimates also show that poor households are more price-sensitive, which implies that their willingness to pay for a given change in utility coming from a better school choice will be lower than that of non-poor households. A third channel that may explain part of the differences is related to the spatial distribution of households and schools in the market, which differs systematically across poor and non-poor households.

5.2.3 Discussion

We have estimated a school choice model and studied a counterfactual exercise by which information on undistorted quality signals is provided to households. Results point in three directions. First, distortions in quality signals have effects in choices, as choice probabilities would change significantly in the counterfactual scenario. Second, households would react to the change in the quality disclosure system mostly by increasing the probability of choosing higher quality schools, while on average the policy would hardly impact average predicted distance between households and schools and average fees paid by households. This is, there would be a shift of students towards relatively high quality schools available in the market. Third, our welfare calculations points towards small average gains across households but large gains for switchers. In both cases, gains are larger for non-poor households, which is driven by them being more quality-sensitive and less price-sensitive. The magnitude of aggregate welfare gains suggests that it may be socially beneficial to invest in quality disclosure systems that reduce the extent of distortions in quality signals in the context of educations markets.

6 Conclusion

Work in progress.
References


Figure 1: Predictability of test scores and attendance on test day

(a) Coefficient estimates and 95% confidence interval from a linear regression of test score on (1) a full set of indicators for a student’s GPA, and (2) school fixed effects. Standard errors clustered at the school level. Gray lines indicate the mean.

(b) Difference in average attendance rate (%) between 4th graders (who take the test) and 3rd graders (who do not take the test) around test days and (black line). Legend: dark blue students above 90th percentile of GPA distribution, light blue above 75th, dark red below 10th, and light red below 25th. Vertical gray lines indicate test days.
Distortion in quality signals ($y$-axis) are defined as (minus) the difference between observed test scores in a school and a counterfactual scenario in which all students in the school take the test. Schools are ordered from lower to higher distortions in the $x$-axis. Vertical lines represent the 95% confidence interval. Green (gray) lines represents distortions that are (not) statistically different from zero. Distortions without confidence interval represent schools in which all students took the test. Approximately 5,000 schools every year.
Figure 3: Distribution of distortions

Histogram of distortions for schools in the period 2005–2013. Distortions are defined as the difference between undistorted quality signals and the observed quality signal. See section 3 for a description of the methodology used to calculate these quantities.
Local polynomial regressions using residuals from a regression on school and year fixed effects ($N = 44,102$). Distortions in quality signals are expressed as percentage of the mean (2.7 test score points), and the other variables are so in terms of their standard deviation.
Figure 5: Monetary incentives for teachers

(a) Distortion in year $t + 1$

(b) Distortion in year $t + 1$

(c) Distortion in year $t + 2$

(d) Distortion in year $t + 2$

Figure 6: “Educational Traffic lights” policy

(a) Distortion in year 2010

(b) Distortion in year 2010
Figure 7: Market definition and example

This map presents the ten largest educational markets in three adjacent regions where 56% of the country’s population lives. Each dot is a school in our data set. An educational market is defined as a cluster of schools in a closed polygon with no other schools closer than 5 kilometers (3.11 miles) from the boundaries. Operationally, a market is uniquely identified from the adjacency matrix of $\Gamma$, where each school is a node. Links in $\Gamma$ are defined as two nodes being closer than 5 kilometers from each other.
Figure 8: Estimated coefficients from the first stage

(a) Poor students, distance
(b) Non-poor students, distance
(c) Poor students, $\delta_j$
(d) Non-poor students, $\delta_j$
Figure 9: Changes in choice probabilities

(a) Poor students, all schools
(b) Non-poor students, all schools
(c) Poor students, chosen school
(d) Non-poor students, chosen school
Figure 10: Changes in school attributes

(a) Distance, poor students

(b) Distance, non-poor students

(c) Price, poor students

(d) Price, non-poor students

(e) Quality, poor students

(f) Quality, non-poor students
Figure 11: Changes in consumer welfare

(a) Average, poor students

(b) Average, non-poor students

(c) Switchers, poor students

(d) Switchers, non-poor students
Table 1: Schools and students

<table>
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<tr>
<th>Panel A: Schools in 2005-2013</th>
<th>Obs.</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>p10</th>
<th>p50</th>
<th>p90</th>
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<td>250</td>
<td>29</td>
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<td>Students per Grade</td>
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<td>7</td>
<td>22</td>
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<td>Voucher</td>
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<td>0</td>
<td>375,000</td>
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<td>66</td>
<td>4</td>
<td>40</td>
<td>177</td>
<td></td>
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<th>Panel B: Students in 2013</th>
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<td>200</td>
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<td>GPA</td>
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<td>5.9</td>
<td>0.6</td>
<td>5.1</td>
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<td>Attendance in test-day</td>
<td>137,604</td>
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<td>1.0</td>
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<td>Attendance in non-test day</td>
<td>137,127</td>
<td>0.92</td>
<td>0.17</td>
<td>0.8</td>
<td>1.0</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Notes: Own construction based on administrative data provided by the Ministry of Education.
Table 2: Data used for estimation

| Year | Market ID | Students | | | Schools | | |
|------|-----------|----------|----------|---|----------|----------|
|      |           | Total    | In Sample | Share SEP | Total | In Sample |
| 2013 | 1         | 3063     | 41.13 %   | 63.33 %   | 55    | 100 %     |
|      | 2         | 4236     | 48.06 %   | 48.33 %   | 75    | 100 %     |
|      | 6         | 2541     | 37.70 %   | 35.80 %   | 30    | 100 %     |
|      | 7         | 5605     | 39.57 %   | 36.97 %   | 73    | 100 %     |
|      | 15        | 2651     | 24.25 %   | 51.47 %   | 34    | 100 %     |
|      | 22        | 5766     | 44.27 %   | 49.54 %   | 137   | 97.81 %   |
|      | 64        | 2492     | 24.35 %   | 61.28 %   | 62    | 79.03 %   |
|      | 69        | 11322    | 29.87 %   | 49.43 %   | 325   | 93.84 %   |
|      | 79        | 1568     | 25.95 %   | 48.15 %   | 45    | 82.22 %   |
|      | 84        | 4186     | 20.71 %   | 44.98 %   | 83    | 81.92 %   |
|      | 120       | 1896     | 26.84 %   | 52.65 %   | 42    | 97.61 %   |
|      | 131       | 3194     | 21.03 %   | 57.58 %   | 59    | 96.61 %   |
|      | 156       | 2796     | 26.60 %   | 54.30 %   | 61    | 86.88 %   |
|      | 174       | 2489     | 30.13 %   | 47.59 %   | 49    | 100 %     |
|      | 188       | 8792     | 30.18 %   | 53.05 %   | 188   | 98.39 %   |
|      | 195       | 2281     | 23.98 %   | 73.30 %   | 50    | 66 %      |
|      | 221       | 4058     | 54.48 %   | 54.00 %   | 92    | 100 %     |
|      | 263       | 2027     | 30.09 %   | 54.59 %   | 46    | 97.82 %   |
|      | 277       | 2172     | 44.06 %   | 58.82 %   | 59    | 100 %     |
|      | 285       | 3133     | 24.92 %   | 61.20 %   | 58    | 100 %     |
|      | 309       | 1696     | 31.54 %   | 28.41 %   | 33    | 100 %     |
|      | 325       | 1164     | 29.38 %   | 65.78 %   | 27    | 96.29 %   |

| 2014 | 1         | 3138     | 40.82 %   | 67.91 %   | 55    | 100 %     |
|      | 2         | 4342     | 48.91 %   | 51.22 %   | 76    | 100 %     |
|      | 6         | 2765     | 38.51 %   | 30.23 %   | 30    | 100 %     |
|      | 7         | 5776     | 35.49 %   | 40 %      | 72    | 100 %     |
|      | 15        | 2667     | 21.97 %   | 47.78 %   | 35    | 97.14 %   |
|      | 22        | 6026     | 41.02 %   | 49.63 %   | 137   | 97.81 %   |
|      | 64        | 2610     | 11.53 %   | 54.81 %   | 64    | 40.62 %   |
|      | 69        | 11535    | 26.42 %   | 51.57 %   | 319   | 94.35 %   |
|      | 79        | 1608     | 25.24 %   | 57.88 %   | 46    | 82.60 %   |
|      | 84        | 4257     | 13.88 %   | 45.51 %   | 82    | 81.70 %   |
|      | 120       | 1947     | 25.47 %   | 56.85 %   | 42    | 95.23 %   |
|      | 131       | 3268     | 16.95 %   | 56.67 %   | 58    | 96.55 %   |
|      | 156       | 2873     | 28.05 %   | 57.44 %   | 61    | 88.52 %   |
|      | 174       | 2557     | 26.94 %   | 51.08 %   | 49    | 97.95 %   |
|      | 188       | 8848     | 25.13 %   | 53.50 %   | 184   | 95.65 %   |
|      | 195       | 2318     | 14.58 %   | 66.56 %   | 50    | 66 %      |
|      | 221       | 4158     | 47.54 %   | 54.72 %   | 94    | 95.74 %   |
|      | 263       | 2052     | 25.24 %   | 59.07 %   | 46    | 100 %     |
|      | 277       | 2265     | 38.67 %   | 54.33 %   | 59    | 98.30 %   |
|      | 285       | 3305     | 21.27 %   | 59.17 %   | 58    | 98.27 %   |
|      | 309       | 1729     | 33.37 %   | 28.42 %   | 33    | 100 %     |
|      | 325       | 1289     | 27.77 %   | 56.70 %   | 29    | 93.10 %   |
### Table 3: Results from second stage of estimation

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
<th>(10)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Price</strong></td>
<td>-0.011***</td>
<td>-0.010***</td>
<td>-0.010***</td>
<td>-0.010***</td>
<td>-0.010***</td>
<td>-0.003***</td>
<td>-0.006***</td>
<td>-0.004***</td>
<td>-0.004***</td>
<td>-0.004***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td><strong>Quality</strong></td>
<td>0.005***</td>
<td>0.005***</td>
<td>0.006***</td>
<td>0.006***</td>
<td>0.006***</td>
<td>0.019***</td>
<td>0.018***</td>
<td>0.015***</td>
<td>0.015***</td>
<td>0.015***</td>
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<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
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<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td><strong>Religious</strong></td>
<td>-0.024</td>
<td>-0.080**</td>
<td>-0.079**</td>
<td>-0.086**</td>
<td></td>
<td>0.076</td>
<td>0.013</td>
<td>0.010</td>
<td>-0.015</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.034)</td>
<td>(0.033)</td>
<td>(0.033)</td>
<td></td>
<td>(0.048)</td>
<td>(0.037)</td>
<td>(0.036)</td>
<td>(0.036)</td>
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</tr>
<tr>
<td><strong>Share poor</strong></td>
<td>0.054</td>
<td>0.108*</td>
<td>0.077</td>
<td>0.120*</td>
<td>-0.461***</td>
<td>-0.507***</td>
<td>-0.485***</td>
<td>-0.406***</td>
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<td>-0.049***</td>
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<tr>
<td></td>
<td>(0.076)</td>
<td>(0.063)</td>
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<td>(0.079)</td>
<td>(0.063)</td>
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<tr>
<td><strong>Distortion</strong></td>
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</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.005)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.005)</td>
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</tr>
<tr>
<td><strong>Market FE</strong></td>
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<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>Y</td>
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<td>Y</td>
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<td><strong>Year FE</strong></td>
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<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
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<tr>
<td><strong>Observations</strong></td>
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<td>2,789</td>
<td>2,789</td>
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<tr>
<td><strong>R-squared</strong></td>
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<td>0.083</td>
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<td>0.416</td>
<td>0.420</td>
<td>0.092</td>
<td>0.104</td>
<td>0.491</td>
<td>0.502</td>
<td>0.517</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
Table 4: Means of predicted school attributes of households’ choices

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Scenario</th>
<th>(1) Poor students</th>
<th>(2) Non-poor students</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance</td>
<td>Baseline</td>
<td>2.394</td>
<td>2.582</td>
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<tr>
<td></td>
<td>Counterfactual</td>
<td>2.395</td>
<td>2.587</td>
</tr>
<tr>
<td>Price</td>
<td>Baseline</td>
<td>7.719</td>
<td>34.614</td>
</tr>
<tr>
<td></td>
<td>Counterfactual</td>
<td>7.634</td>
<td>34.494</td>
</tr>
<tr>
<td>Quality</td>
<td>Baseline</td>
<td>253.347</td>
<td>263.457</td>
</tr>
<tr>
<td></td>
<td>Counterfactual</td>
<td>260.163</td>
<td>271.190</td>
</tr>
</tbody>
</table>
A Theoretical Model

We consider the case of a market in which \( J \) heterogeneous schools compete for the demand of \( M \) consumers by providing services.

**Information.** We consider a context in which quality disclosure by schools is mandatory, but in which schools have the ability to distort quality signals with respect to effective quality in order to influence demand for the services they offer. Consumers in this market value quality of services provided by schools, \( q_j \), although they imperfectly observe it. In fact, they only observe \( v_j = q_j + \psi_j \), where \( q_j \) is schools’ effective quality and \( \psi_j \) is a distortion introduced by schools in order to signal higher quality.

**Demand.** Consumers in the model are households that choose to purchase one unit of schooling services from one of the schools available in the market. Households derive utility from both the price \( p_j \) and perceived quality \( v_j \) of schooling services. Consumers are assumed to be *naive*, and therefore do not make inference on the observed quality signals in order to extract the level of effective school quality. Therefore, we can think of demand for school \( j \) in this context as the probability that a given household chooses such school scaled up by the size of the market, \( M \), which is \( MD_j = MD_j(p, v) \).

**Schools.** Schools are profit maximizing firms. They obtain revenue from school fees and face three costs. The first one is the cost of providing school services, which is indexed on the quality of services provided, \( c_j(q_j) \), with \( c'_j(q_j) > 0 \). Note that (i) marginal cost is constant for a given level of quality, and that (ii) the marginal cost function varies across schools, concentrating the heterogeneity across them. The second is the cost of distorting the observed quality signal by consumers, \( A(\psi_j, MD_j) \), with \( A_1(\psi_j, MD_j) > 0 \) and \( A_2(\psi_j, MD_j) > 0 \).\(^{19}\) The reason why this cost depends on demand for the school is that we argue that the larger the number of students served by the school, the costlier will be for it to distort its quality signal. The third one is a sunk entry cost, \( c_e \), which will pin down the equilibrium number of schools in the market. Therefore, an operating school’s profits are given by:

\[
\Pi_j = \max_{p_j, q_j, \psi_j} MD_j(p, v)(p_j - c_j(q_j)) - A(\psi_j, MD_j(p, v))
\]

such that profits will depend on all schools’ prices, effective quality levels and distortions.\(^{20}\)

\(^{19}\)We think of this function as the inverse of the production function of the distortion \( \psi_j \), which has as inputs the amount of resources \( A_j \) and demand \( MD_j \). If such function is strictly increasing in \( A_j \), then we can invert it and write \( A(\psi_j, MD_j) \), which measures the value of the resources required for implementing distortion \( \psi_j \) for a given level of demand \( MD_j \).

\(^{20}\)Note that this profit function could accommodate schools that do not have the ability to modify fees (i.e.
Schools’ Behavior. The first order conditions from the school problem with respect to price, quality and distortion are respectively given by:

\[
M \frac{\partial D_j}{\partial p_j} (p_j - c_j(q_j)) + MD_j - A_2(\psi_j, MD_j)M \frac{\partial D_j}{\partial p_j} = 0 \quad (11)
\]

\[
M \frac{\partial D_j}{\partial v_j} (p_j - c_j(q_j)) - MD_j c_j'(q_j) - A_2(\psi_j, MD_j)M \frac{\partial D_j}{\partial v_j} = 0 \quad (12)
\]

\[
M \frac{\partial D_j}{\partial v_j} (p_j - c_j(q_j)) - A_1(\psi_j, MD_j) - A_2(\psi_j, MD_j)M \frac{\partial D_j}{\partial v_j} = 0 \quad (13)
\]

where several aspects should be noted. First, note that increasing the price has an additional effect in that by reducing demand for the school, it reduces the cost of the distortion \( \psi_j \).

Rearranging the first equation we get an expression for price as:

\[
p_j = c_j(q_j) + A_2(\psi_j, MD_j) + D_j \left[-\frac{\partial D_j}{\partial p_j}\right]^{-1}
\]

which shows that the firm will charge a mark-up over its marginal cost of production and its marginal cost of distorting the quality signal, which is decreasing in the price-sensitivity of demand. Second, note that given that \( q_j \) and \( \psi_j \) equally affect the quality perceived by households, the marginal revenue that the school’s will get from them is actually the same. In fact, combining (12) and (13) we obtain that:

\[
MD_j c_j'(q_j) = A_1(\psi_j, MD_j)
\]

and therefore that schools will choose levels of quality and distortion such that their respective marginal costs are made equal in equilibrium. Third, note that the distortion is costly to schools in two dimensions. First, it has a direct cost, through increasing \( \psi_j \) and therefore \( A \). Second, by increasing demand for the school, it also increases the cost through the scale effect mentioned above.

Equilibrium. All schools in the market will operate optimally according to equations (11), (12) and (13) above. The equilibrium number of schools in the market will be determined by the fact that no school would operate if it were to obtain negative profits from it. This public schools in our context) by constraining \( p_j \) to some given level. A stronger caveat to this formulation would be associated to whether or not those schools behave as profit maximizing firms or not.

21 We would be able to do the same for quality if we imposed some assumption on \( c_j(q_j) \). For instance, if we let \( c_j(q_j) = c_j q_j \), we get:

\[
q_j = \frac{p_j - A_2(\psi_j, MD_j)}{c_j} - D_j \left[\frac{\partial D_j}{\partial v_j}\right]^{-1}
\]

where the second term is reduced as the quality-sensitivity of demand increases.
implies that in equilibrium, if we order schools according to their profits, the following condition must hold:

\[ \Pi_{J^*} \geq c_e \geq \Pi_{J^*+1} \]

where \( \Pi_{J^*} \) are the profits of the \( J^* \)th school in the market.

**Comparative Statics.** We are working in computing the comparative statics of the model. Our objective with them is to try to understand cross-sectional heterogeneity in school behavior that we observe in the data. The comparative statics we are interested on are:

- How does market size \( M \) affect the number of schools in the market \( J^* \)? Moreover, how does it affect the other outcomes?
- We can specify \( c_j(q_j) \) (e.g. \( c_j(q_j) = c_j q_j \)) and show how equilibrium outcomes depend on \( c_j \), which can be interpreted as some underlying heterogeneity in productivity across schools.
- We can also specify a parameter in the demand that measures the relative preference for quality over price, \( \theta \), and show how equilibrium outcomes depend on this parameter.
- Finally, an exercise that may be tougher would be to analyze how equilibrium outcomes depend on the variance of \( c_j \) at the market level, which is presumably linked to measures of the intensity of competition.