Appendix for Online Publication

Distorted Quality Signals in School Markets

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A More about Estimating Distortions

A.1 Robustness of Distortions

In this appendix, we develop a variety of exercises in order to assess the robustness of distortions in school test scores, estimated as discussed in Section 4.1.

Model specification for estimation of distortions. Two statistical exercises provide support for the specification in equation (3). First, the R-squared of the 7,500 linear regressions we estimate are high (approximately 0.51) and are always higher in the polynomial rather than the linear model, as shown in Figure A.10. Second, we implement a cross-validation exercise in which we assume test takers are the universe of students and we proceed to delete the test scores of ten percent of students with low GPA, essentially mimicking real world patterns. Reassuringly, in this exercise the quadratic polynomial specification has a lower mean squared error than the linear model. In addition, predicted test scores are similar to observed test scores for students with low and high academic performance, as displayed by Figure A.11.

Accounting for selection into test day. A concern with equation (3) is that of selective attendance. To test for selection, we re-estimated this equation using a Heckman selection correction and found evidence supporting our model. The excluded variable when calculating the Heckman corrected distortions is an indicator for students living outside of the school's county, which effectively predicts attendance on test days. These Heckman corrected distortions are remarkably similar to the uncorrected ones –but noisier, as expected– and both are highly correlated, as displayed by Figure A.12. Finally, our cross validation exercise shows remarkably similar results for both models in terms of mean squared error. Given this evidence, we utilize distortions estimated without this selection correction.

Distortions are independent from noise in test scores. Measurement error (i.e. noise) can also cause discrepancies between observed and true quality signals. However, we emphasize that (1) noise is a mean zero random error that is mean independent of distortions, and (2) distortions are policy-relevant while noise is not. As our setting allows us to calculate the variance of noise in school test scores, we can show the former empirically. We construct a noise distribution for each school in our data using administrative estimates of noise in student-level test scores. These estimates are called "individual-level variability in test scores" and can be aggregated to construct measures of school-level noise following the method in Quality Education Agency (2013). Figure A.13 shows that noise is uncorrelated with distortions (correlation is 0.02), which supports the notion that our analysis of test day attendance represents a different margin that distorts quality signals.

B Understanding Distortions in Quality Signals

B.1 Schools' Characteristics

Fixed School Characteristics. A significant share of the variation in distortions is explained by school time-invariant characteristics. If we regress distortions on school indicators, we can explain 36 percent of the variance. If we restrict attention to schools with statistically positive distortions, we can explain 60 percent of the variance. These percentages are large, especially considering that the maximum variation that can be explained is probably lower than one due to measurement error in the dependent variable. Which characteristics of schools predict distortions? Consider the following regression:

$$\psi_{jt} = X'_{jt}\theta + \nu_{mt} + \varepsilon_{jmt}$$

where X_{jt} is a vector of school attributes in year t and ν_{mt} is a market-year fixed effect. Markets are defined as isolated groups of schools, i.e., with no schools closer than 3 miles as discussed in section 5.1.3. In order to account for the uncertainty in ψ_{jmt}, we present estimates weighted by (the inverse of) the 95 percent distortion confidence interval, thus accounting for the uncertainty associated to each distortion.

Results are presented in Table A.6-A and show that distortions are larger in small public schools, for-profit schools, schools serving relative low-income households, and schools with low attendance rates. These correlations are larger in schools with distortions that are statistically different from zero. Additionally, Table A.6-B presents the auto-correlation of distortions, which is always positive and statistically different from zero. This positive auto-correlation serves as additional evidence that distortions are non-random but rather associated to school characteristics.

Time-varying School Characteristics. We study whether variation in distortions can be explained by within-school-variation in observable characteristics including school fees, socioeconomic composition, undistorted quality, and measures of attendance and class size. In particular, we estimate:

$$\psi_{jt} = \beta X_{jt} + \eta_j + \nu_t + \varepsilon_{jt} \qquad (11)$$

where X_{jt} is the covariate of interest, and η_j and ν_t are school and time fixed effects. Figure A.14 show basically no relationship between any of these variables and distortions.[34]

B.2 Competitive Environment

The above results suggest that a substantive part of the distortions is explained by schools' fixed characteristics. Now we study whether part of the distortions can be explained by strategic behavioral responses. The first idea to explore is whether larger distortions are associated with the incentives that market environment creates for schools to signal higher quality (Shleifer, 2004). The market-oriented nature of the system suggests that schools facing more competition might choose to increase their quality signals using distortions. Dorfman and Steiner (1954) provide a useful framework to study firm behavior in contexts in which price and quality are jointly determined. The authors show that firms offer higher quality when facing more quality elastic consumers.[35] This section tests for this "quality elasticity" and related hypotheses.

We exploit within school variation in variables related to the competitive environment. We proceed by estimating regressions following equation (11). The variables we consider include the number of schools in the market, average quality, fees and distortion of rivals, and the position of a school in the distribution of fees and quality in the market. We also employ the estimates from our school choice model in section 5 to calculate quality demand elasticities. Figure A.15 displays results graphically. Although changes in the number of schools in the market and changes in average attributes of competitors are uncorrelated with distortions, demand quality elasticity is strongly correlated with distortions. The latter result is consistent with Dorfman and Steiner (1954): schools facing higher quality elasticity optimally choose to signal higher quality. This result is reinforced by the fact that schools in higher percentiles of the market-level quality distribution also seem to introduce higher distortions.

Similarly, the extent to which schools may increase test scores through differential attendance on test days could be one of the drivers of distortions. We construct a measure of potential gains from non-random attendance on test days by comparing predicted school test scores a school

[34]The only clear relationship is that between the number of students missing on test days and the magnitude of the distortion, which is positive as expected: missing students are a necessary condition for this distortion.

[35]Dorfman and Steiner (1954) analyze the behavior of a monopolist and argue that quality is optimally set following the condition:

$$q = \frac{p}{c_q}\frac{\eta^q}{\eta^p}$$

where q is quality, p is price, c_q is the cost of quality, and η^q and η^p are the quality and price demand elasticities, respectively. In our interpretation, however, we use their result to approximate the case of imperfect competition with multiple firms and the analysis of a particular firm facing residual demand which is one way of modeling school behavior in this market setting (Neilson, 2017a). In our setting, we argue that observed quality q can be increased by either increasing true quality or introducing higher distortions.

would obtain if the ten percent of students in the bottom of the GPA distribution was absent on test day with the predicted school test scores if all students attended such day. Figure A.16 displays the correlation between estimated distortions and this measure of potential gains, which is strong and positive: schools that gain more from non-random attendance on test days also display higher distortions.

B.3 Incentives Placed by SEP Voucher Program

We describe the SEP program in section 2 of the paper. The program generates incentives to raise average test scores through two channels associated with the government funding it provides. In particular, incentives placed by the SEP program operate through a classification of schools that is based largely on SIMCE test scores. This classification then determines (i) the degree of autonomy that schools are provided in spending government funding offered by the program, such that schools with higher test scores have more flexibility than those with lower test scores; and (ii) the renewal of the affiliation of schools to the program after four years in it also depends on SIMCE test scores. For a detailed discussion of the program, see Correa et al. (2014).

The program started in 2008, and while almost all public schools adopted the program immediately, private schools were allowed to choose if and when to adopt it and did so in a staggered fashion across subsequent years. The share of voucher schools in the program increased from 46 percent to 69 percent between 2008 and 2013. We exploit this variation in the timing of adoption of the SEP program by schools to study whether such event has an effect on distortions in quality signals. In particular, we estimate the following event study specification:

$$\psi_{jt} = \sum_{\tau=\underline{\tau}}^{\bar{\tau}} \beta_\tau D_{jt,\tau} + X'_{jt}\theta + \eta_j + \nu_t + \varepsilon_{jt} \tag{12}$$

where $D_{jt,\tau}$ is a dummy that indicates that school j adopted the SEP program τ years before year t, such that β_τ's are the parameters of interest, which measure the effect of SEP adoption τ years after adoption. This specification includes school and year fixed effects, and a vector of time-varying school control variables which includes school enrollment, average attendance rates and number of students taking the SIMCE test.

Figure A.17 presents the results from this analysis. We find that after schools adopt the SEP program, they increase their distortions in quality signals by around 0.7 points (0.17σ). This increase persists four years after adopting the program. These results suggest that pressures associated with the SEP program may induce schools to introduce distortions in their test scores in order to comply with requirements set by the SEP program for renewing affiliation with it and continue receiving additional government funding.[36] We interpret these results with caution, given that adoption of the SEP program is a choice of schools (in particular, for voucher schools) and therefore program adoption could be correlated with school unobservables also driving distortions. However, the pre-trend leading to adoption is remarkably well behaved, which limits that concern. These results are consistent with recent work by Feigenberg et al. (2018), Quezada-Hofflinger and Von Hippel (2018) and Sánchez (2019).

B.4 Monetary Incentives for Teachers

We describe the SNED program in section 2 of the paper. 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:

$$\psi_{jt} = \mathbf{1_{IN}} f^{IN}(\text{SNED}^{IN}_{jt-1}) + \mathbf{1_{OUT}} f^{OUT}(\text{SNED}^{OUT}_{jt-1}) + \eta_j + \nu_t + \varepsilon_{jt} \tag{13}$$

where SNED^{IN}_{jt-1} measures distance to the threshold for winners, and SNED^{OUT}_{jt-1} 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, we would interpret it as evidence of teachers introducing distortions to test scores as a response to the incentives placed by the program.

Figure A.18 presents four 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 provide suggestive evidence against the hypothesis that teachers manipulate attendance to increase test scores.

[36] The implementation of the SEP program was not as rigorous as intended. In fact, the first sanctions to schools were implemented in 2012, several years after the program started (Neilson, 2017b). These results suggest that, regardless of difficulties with the implementation, schools at least partially believed that MINEDUC would behave in accordance to the design of the program according to sanction, as in absence of such belief there would have been no additional pressure on schools regarding increasing test scores and, therefore, no increase in distortions in quality signals.

B.5 Information for School Choice

Other quality disclosure policies could incentivize schools to introduce distortions in quality signals, as is the case of the ETL informational policy, which we use to test for this mechanism. See section 2 of the paper for details about the program.

Following the discontinuous incentives at the threshold, we estimate:

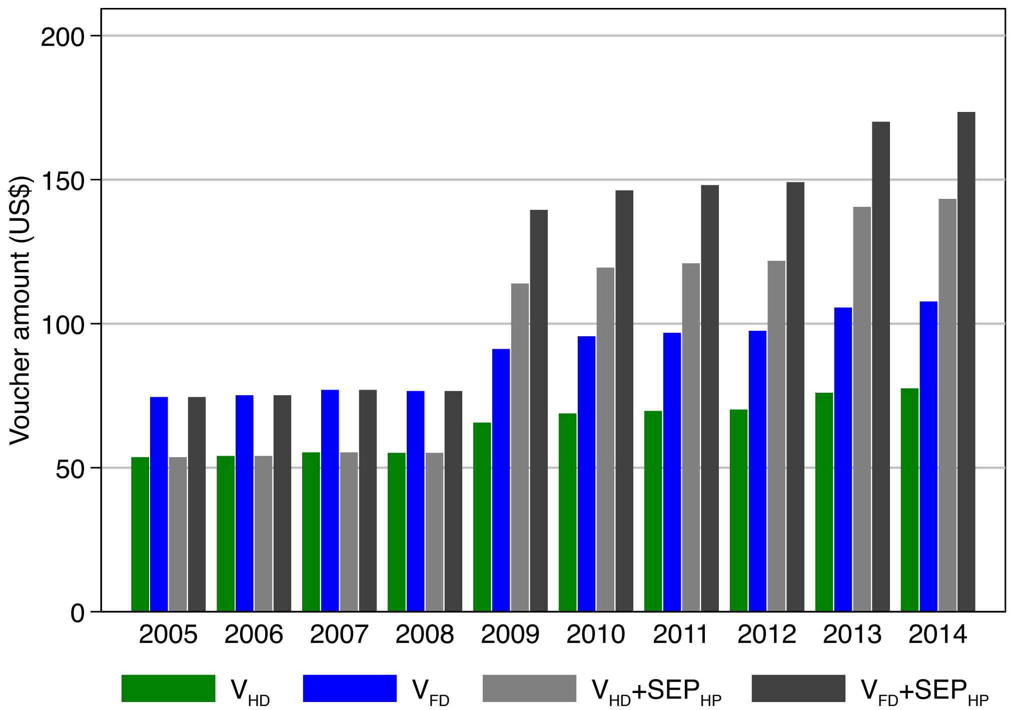
$$\psi_{jt} = \mathbf{1_r} f^r(q_{jt-1}) + \mathbf{1_y} f^y(q_{jt-1}) + \mathbf{1_g} f^g(q_{jt-1}) + X'_{jt}\theta + \varepsilon_{jt} \tag{14}$$

where q_{jt-1} measures test scores with which the ETL policy was assigned to schools. Our objects of interest are the functions f^r, f^y and f^g, where r, y and g stand for the three different quality levels signed by the policy to schools. If schools closer to the policy thresholds have larger distortions, we would interpret it as evidence of schools introducing distortions in order to signal a higher level of quality in a subsequent version of the policy.

Figure A.19 presents the linear relationships between test scores and distortions around the ETL policy cutoffs. Again, we present results for distortions and residualized distortions.[37] These plots show that distortions increased slightly 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. Note that once school characteristics are controlled for, this pattern can hardly be noticed. This pattern, however, is not the same around the second cutoff. These results do not provide strong evidence that schools closer to thresholds set by this policy introduce higher distortions in order to signal higher quality.

[37]Note that this is a cross-sectional exercise, so we cannot include school and year fixed effects in this case, just school characteristics.

Figure A.1: Evolution of vouchers



Notes: Amount covered by different types of vouchers in the system. In particular, four types are displayed, covering the interaction of schools offering half and full school shifts (i.e. HD and FD) according to the JEC program, and school subscribed and not subscribed to the SEP program. This figure displays the voucher amount for SEP school with high performance. Note that this figure do not display all voucher types: the voucher amount for low performing SEP schools and the component of SEP vouchers related to the concentration of SEP students in schools are not reported.

Figure A.2: Test scores as quality signals

"La Segunda" te invita al cine a precios rebajados
CUPONES EN PAGINA 46
Segunda
EXCLUSIVO En la Región Metropolitana
RESULTADOS DEL SIMCE
COLEGIO POR COLEGIO

(a) Public dissemination of test scores

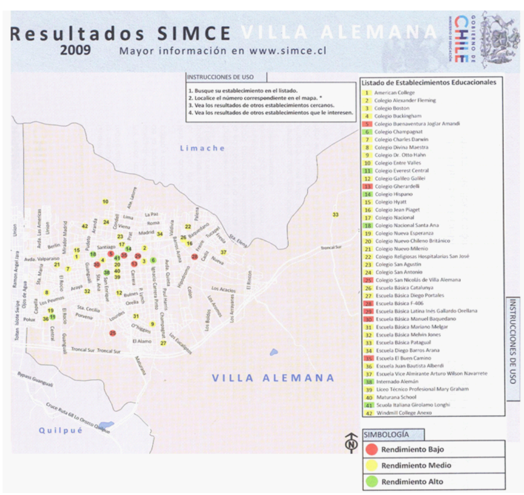
4º Básico Los 50 colegios con mejor Simce

	Establecimiento	Comuna	Dep.	Lenguaje	Matemática	C. Medio Natural	Prom. leng. y matemat.
1	Colegio La Girouette	Las Condes	PP	336	328	332	332,0
2	Colegio San Jorge	Laja	PP	316	345	328	330,5
3	Escuela Básica Madrigal	La Reina	PP	329	329	322	329,0
4	Colegio Curimon	San Felipe	PP	335	322	330	328,5
5	Colegio The Grange School	La Reina	PP	326	324	322	325,0
5	Colegio Kendal English School	Ñuñoa	PP	325	325	316	325,0
7	Colegio Redland School	Las Condes	PP	329	320	307	324,5
7	Colegio Cambridge College	Providencia	PP	327	322	327	324,5
7	Colegio Santiago College	Providencia	PP	331	318	313	324,5
10	Colegio Arauco	Arauco	PP	317	331	322	324,0
10	Colegio Constitución	Constitución	PP	314	334	315	324,0
12	Colegio Itahue de Chiguayante	Chiguayante	PP	317	329	314	323,0
13	Escuela Básica, Colegio Peñalolén	Peñalolén	PP	325	320	314	322,5
13	Colegio Montemar	Viña del Mar	PP	323	322	317	322,5
13	Colegio San Joaquín	La Serena	PP	317	328	316	322,5
16	Colegio Pucón Nevados	Pucón	PS	319	325	307	322,0
17	Souther Oxford School	Villarrica	PP	313	330	316	321,5
18	Colegio Internacional Alba	Maipú	PP	321	321	319	321,0
18	Colegio de La Salle	La Reina	PP	321	321	316	321,0
18	Colegio Arrayanes	San Fernando	PP	323	319	324	321,0
21	Colegio Mozart Schule	Concepción	PP	322	319	301	320,5
22	Colegio Cumbres	Las Condes	PP	317	322	311	319,5
23	Colegio Villa María Academy	Las Condes	PP	320	318	296	319,0
24	Colegio P. Hurtado y Juanita de los Andes	Las Condes	PP	320	317	308	318,5
24	Colegio San Benito	Vitacura	PP	315	322	288	318,5
26	Colegio Andrée English School	La Reina	PP	315	321	330	318,0
26	Inst. de Humanidades Alfredo Silva S.	Concepción	PP	319	317	314	318,0
26	Colegio Alborada	Linares	PP	318	318	304	318,0
26	Saint Paul's School	Viña del Mar	PP	321	315	302	318,0
30	Colegio Buin	Buin	PP	317	317	318	317,0
30	Escuela Básica Trupam	Conchalí	PS	313	321	301	317,0
32	Colegio Akros S.A.	Ñuñoa	PP	319	314	305	316,5
32	The Wessex School	Concepción	PP	325	308	306	316,5
34	Colegio los Andes de Vitacura	Vitacura	PP	319	312	310	315,5
34	Complejo Educacional San Crescente	Castro	PS	305	326	282	315,5
34	Cerro Estanque	Tomé	MD	319	312	296	315,5
34	Colegio Quimahue	Rancagua	PP	311	320	315	315,5
38	Colegio San Ignacio	Calama	PP	299	331	321	315,0
38	Colegio Saint George's College	Vitacura	PP	317	313	302	315,0
38	Colegio Eduardo Martín Abejon	Constitución	PS	331	299	281	315,0
41	Colegio The Antofagasta British School	Antofagasta	PP	315	314	312	314,5
42	Colegio Saint Gabriel's	Providencia	PP	317	311	302	314,0
43	Colegio Pedro de Valdivia Las Condes	Las Condes	PP	313	314	307	313,5
43	Colegio Wenlock School	Las Condes	PP	316	311	286	313,5
43	Colegio Particular Montessori	Talca	PP	318	309	306	313,5
43	Colegio de los Sagrados Corazones	Valparaíso	PP	312	315	312	313,5
47	Colegio del Sagrado Corazón de Apoquindo	Las Condes	PP	314	312	304	313,0
47	Instituto Miguel León Prado	San Miguel	PS	315	311	315	313,0
47	Colegio Vedruna	San Felipe	PS	320	306	307	313,0
47	Scuola Italiana Arturo Dell'Oro	Valparaíso	PP	315	311	313	313,0

Fuente Simce

(b) Test scores in newspaper

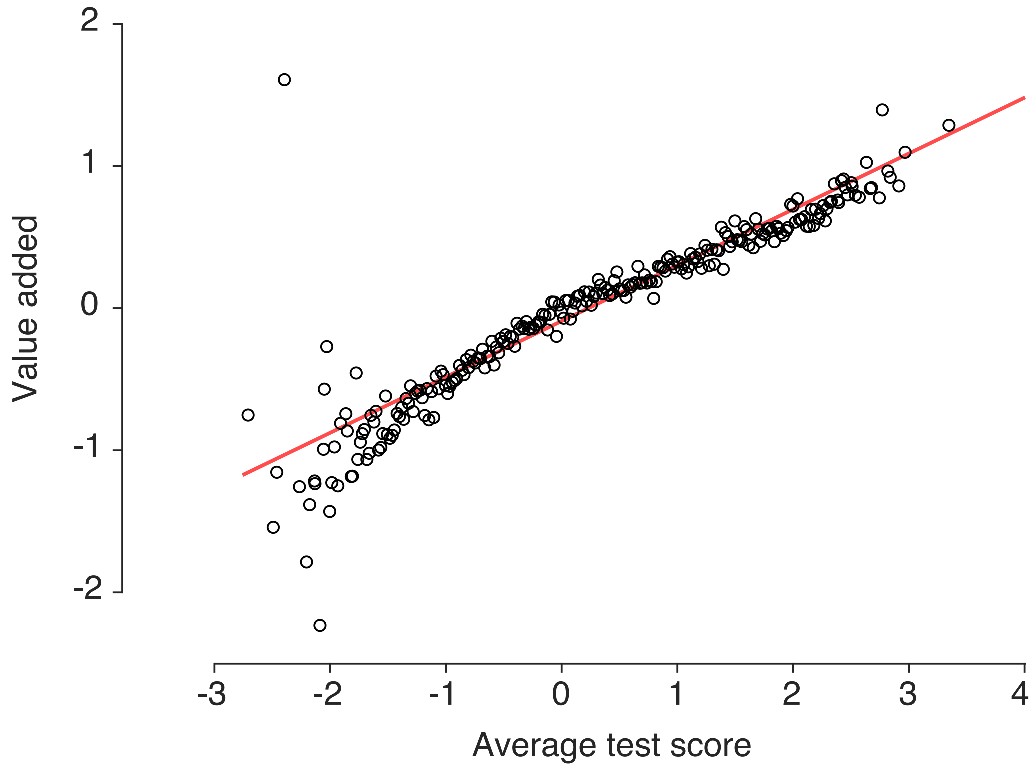
(c) Test scores as an advertising device



(d) Test scores as a policy tool

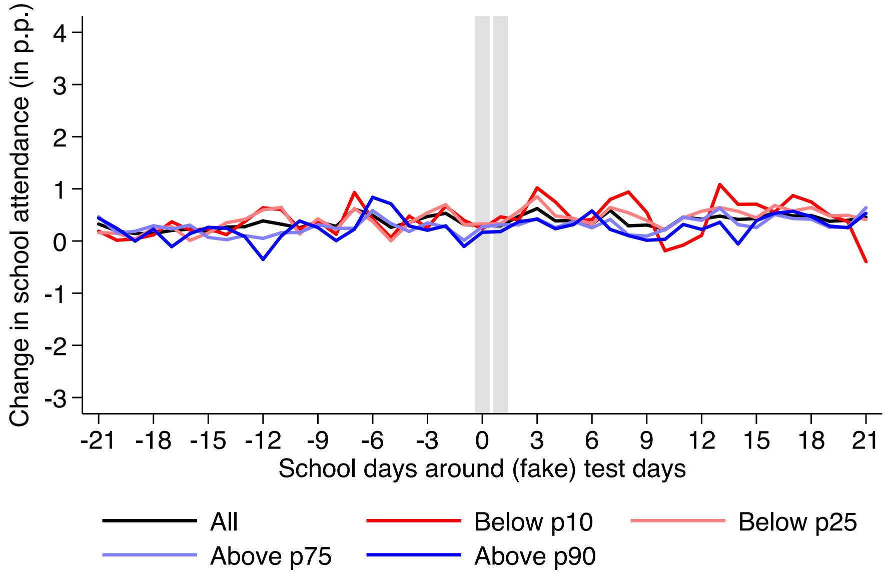
Notes: This figure displays the different roles of test scores in the Chilean educational system. Panel (a) displays the front page of *La Segunda*, a popular newspaper, advertising the disclosure of school level test scores for all schools. Panel (b) shows schools' test scores as published in newspaper *El Mercurio*. Although test scores are observable, other variables such teacher wages, teacher quality, value added, and school composition, are not. Panel (c) displays an advertising banner placed on the front of a school reporting on successful results obtained by the schools in SIMCE as a means of advertising its quality to households. Panel (d) displays an example of of the Educational Traffic Lights policy, which utilizes SIMCE test scores as an input for quality disclosure.

Figure A.3: Correlation between test scores and value added

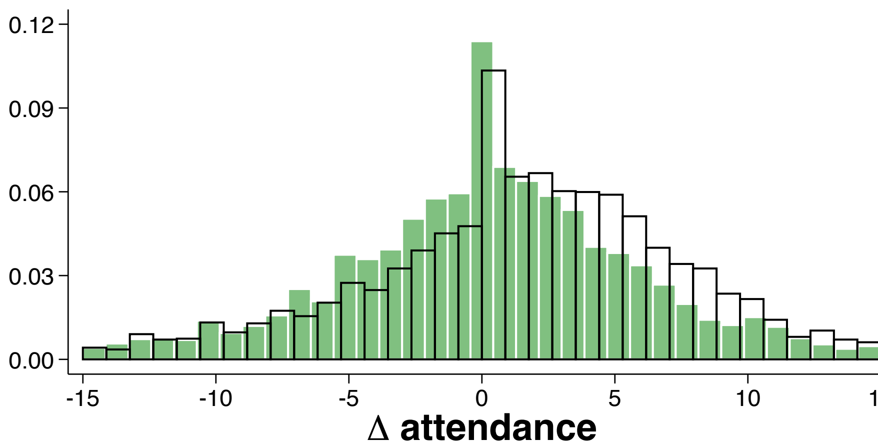


Notes: This figure displays the relationship between test scores and the only available measure of value added in Chile, from Neilson (2017a). We thank the author for providing us with this figure.

Figure A.4: Comparison of school absenteeism on test day with fake test days



(a) Differences-in-differences using school days around April 23th, 2013



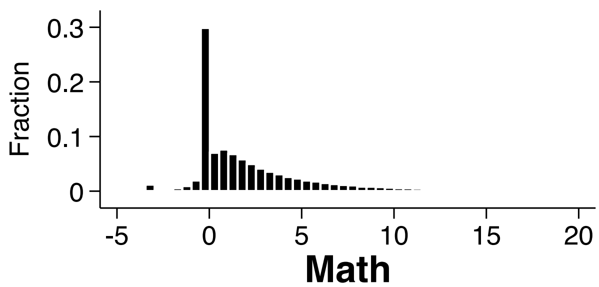
(b) Comparison of distributions (green is April 23th and white are actual test days)

Notes: Panel (a) presents the difference in absenteeism rates between 4*th* and 3*rd* graders across the GPA distribution around April 23th of 2013, a day without standardized tests. The histograms in panel (b) represent the distribution of the following differences-in-differences estimate at the school level:

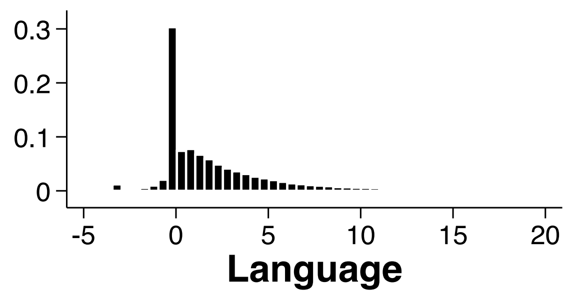
$$\Delta\overline{A}_j = (\overline{A}_{j4T} - \overline{A}_{j4t}) - (\overline{A}_{j3T} - \overline{A}_{j3t})$$

where $\overline{A}_{jkt}$ is the average absenteeism rate of k*th* graders in school j in day t. Day $t = T$ represents the day of the event analyzed (green is April 23th and white actual test days). A Kolmogorov-Smirnov test rejects the equality of distributions in both cases (p-values < 0.01).

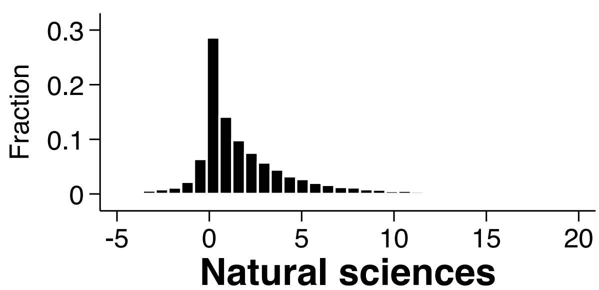
Figure A.5: Distribution of distortions by subject in 4*th* grade



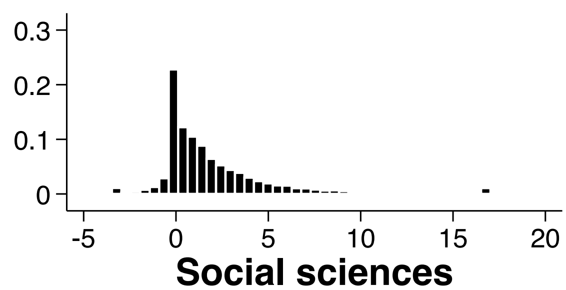
(a) 4*th* grade



(b) 4*th* grade



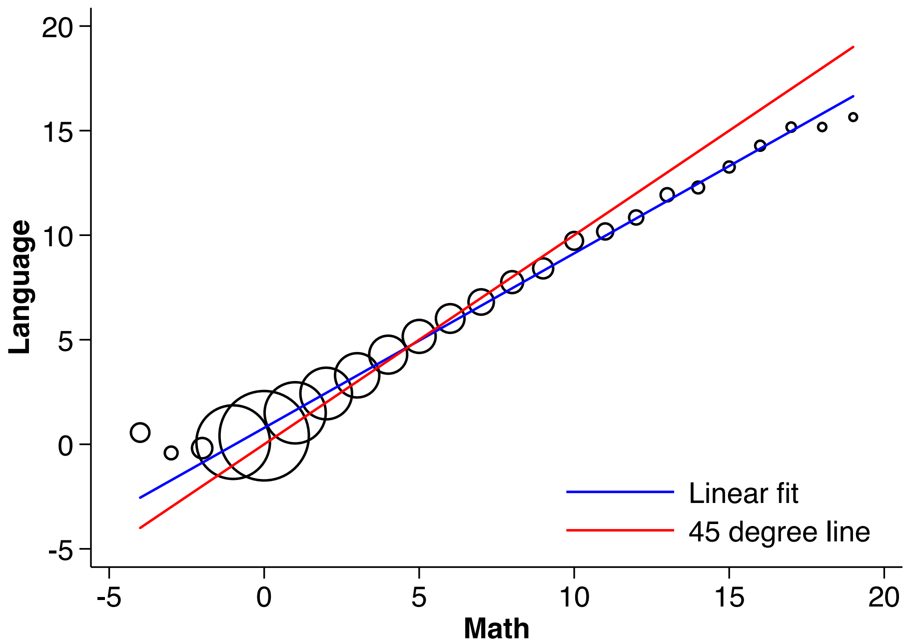
(c) 4*th* grade



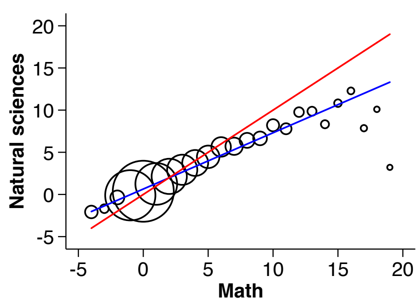
(d) 4*th* grade

Notes: We estimate distortions by subject of SIMCE using the methodology described in section 4 of the paper. Distortions in quality signals correspond to the average distortion in math and language. We provide descriptive statistics for distortions by subject in Table A.1.

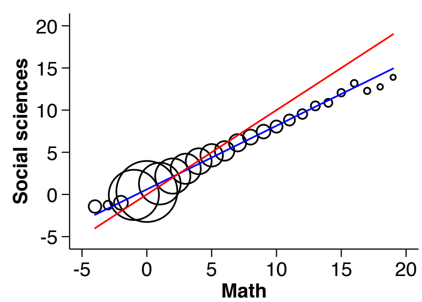
Figure A.6: Correlation between distortions in different tests



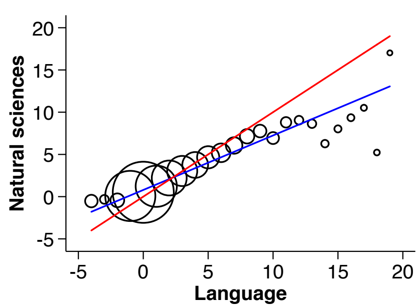
(a) Main tests



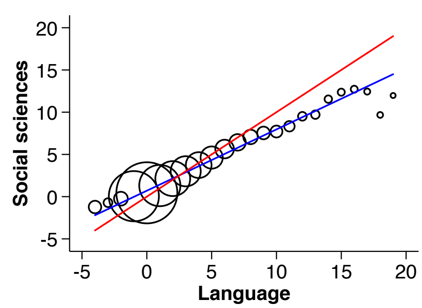
(b)



(c)



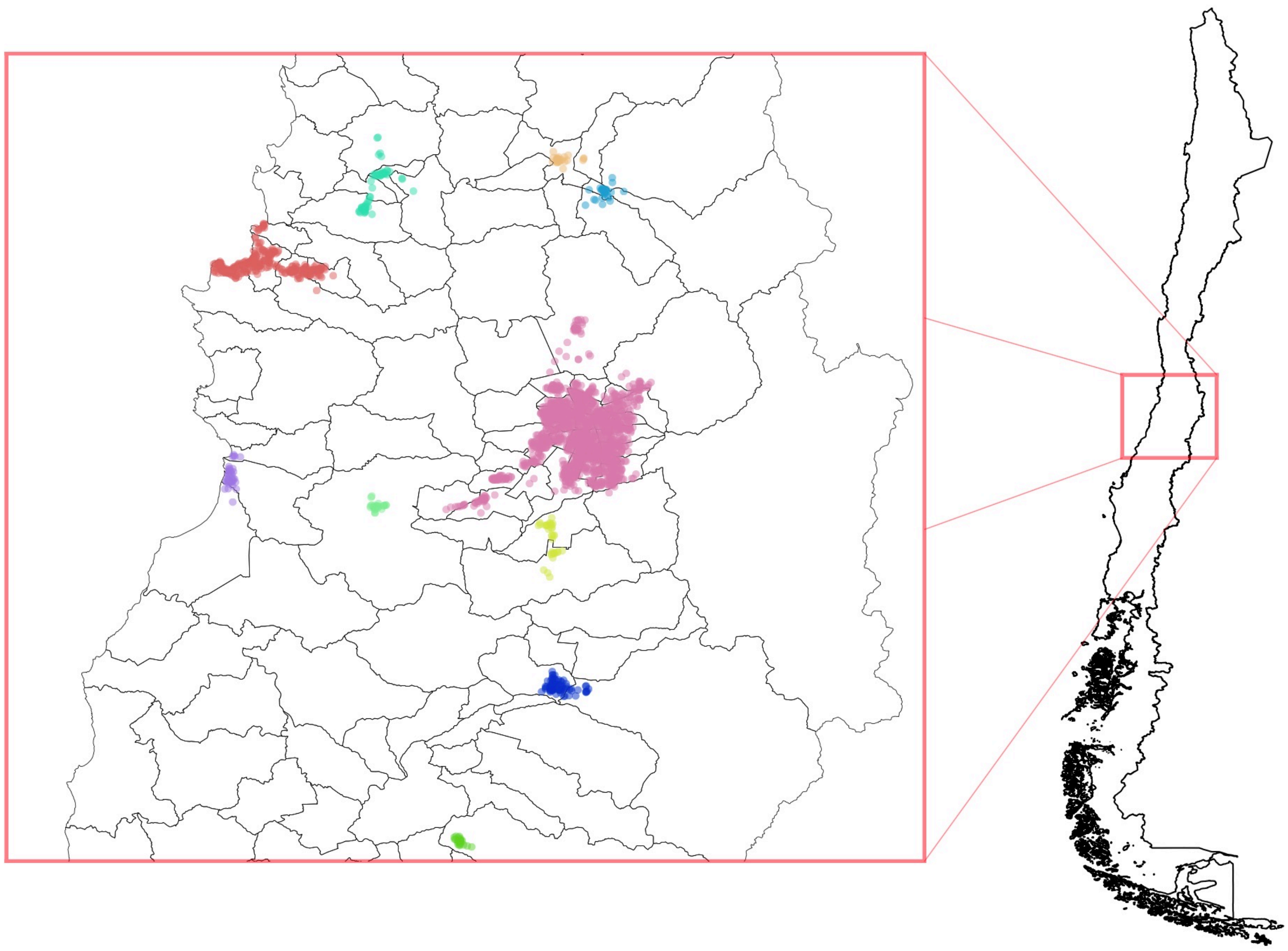
(d)



(e)

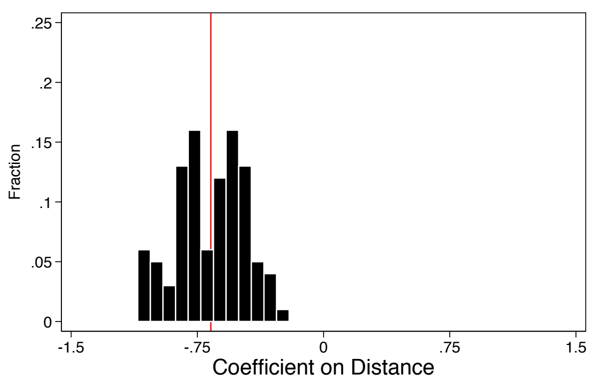
Notes: These figures displays the relationships between estimated distortions in test scores for different subjects of SIMCE.

Figure A.7: Market definition

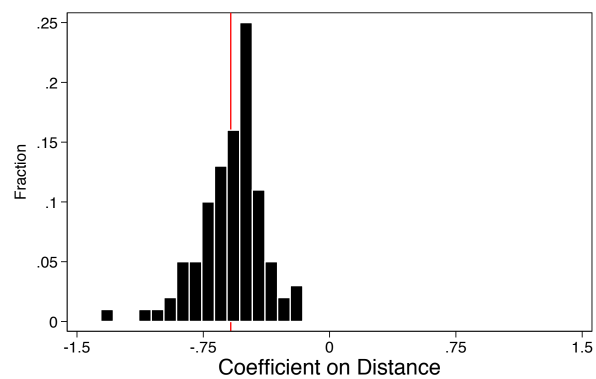


Notes: See description of Table A.2 for details about market definition. This map plots the ten largest markets in the most populated area of the country.

Figure A.8: Estimated coefficients on distance from the first stage



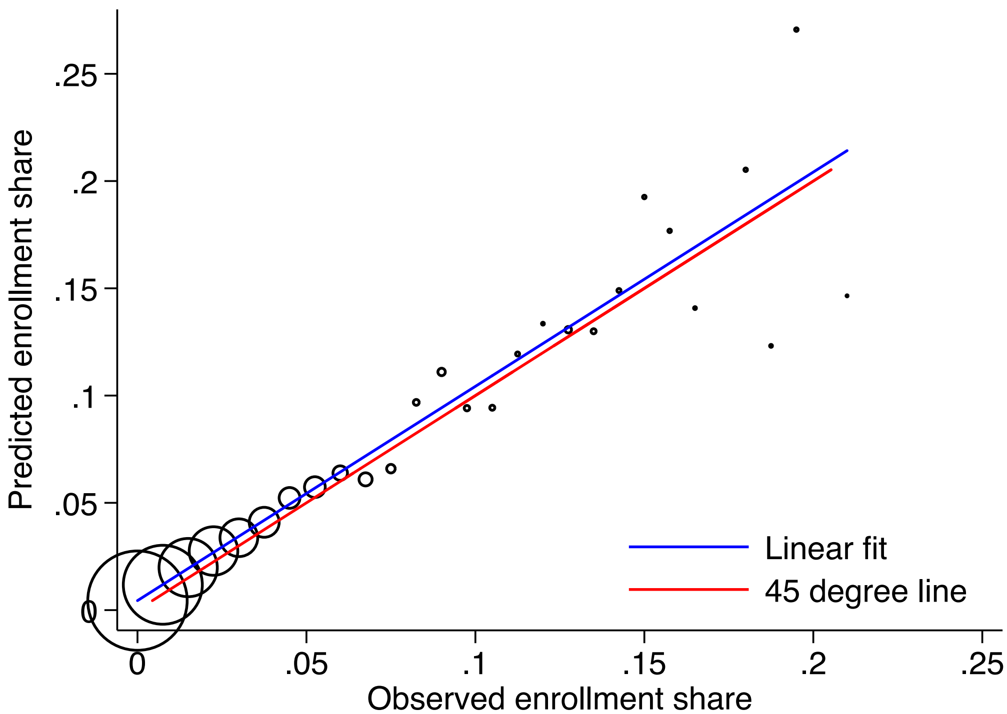
(a) Low-income students, distance



(b) High-income students, distance

Notes: These figures display resulting estimates for β_d^r from the first stage of the school choice model. Each observation is the estimated coefficient for an estimating cell comprised by a market, year and household type. The red line indicates the average coefficient.

Figure A.9: Observed and predicted school enrollment

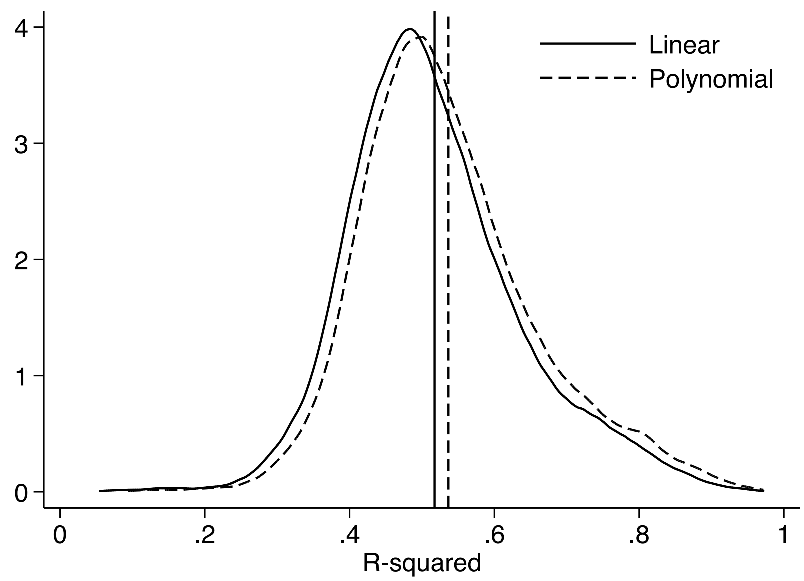


Notes: This figure displays the relationship between observed school enrollment shares and predicted school enrollment shares using model estimates. Predicted enrollment shares are calculated as:

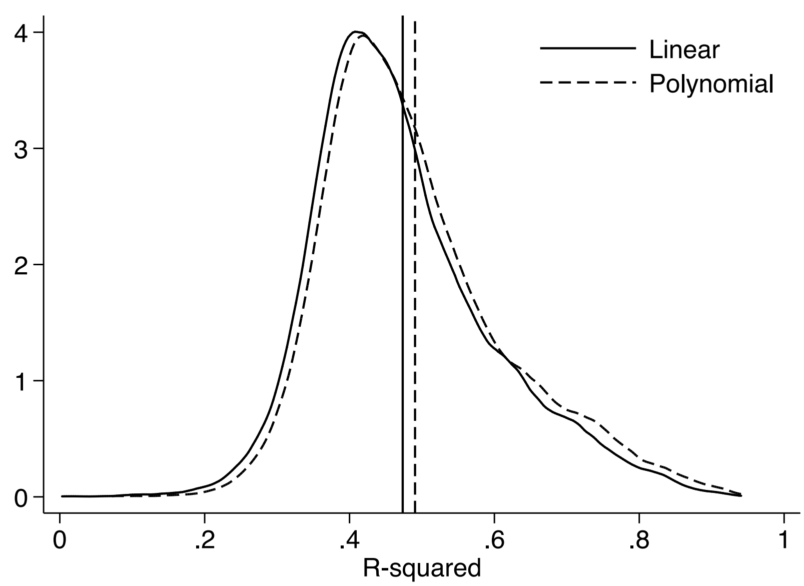
$$s_{jmt}(\hat{\delta}, \hat{\beta}_d) = \sum_r \pi^r_{mt} \frac{1}{N^r_{mt}} \sum_{i \in \mathcal{I}^r_{mt}} P^r_{ijmt}(d^r, \hat{\delta}^r, \hat{\beta}^r_d)$$

where π^r_{mt} is the share of households of type r in market m and year t, while N^r_{mt} and $\mathcal{I}^r_{mt}$ are the number and the set of such households respectively. The expression is thus simply a type-share-weighted average of average choice probabilities for school j.

Figure A.10: Prediction model



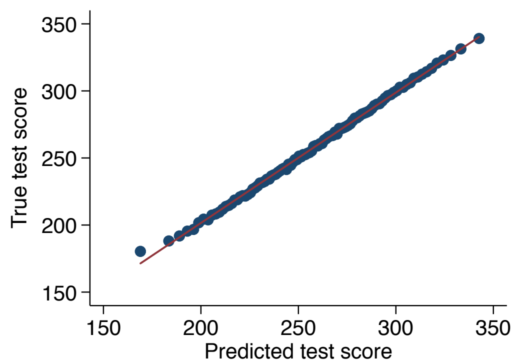
(a) Math



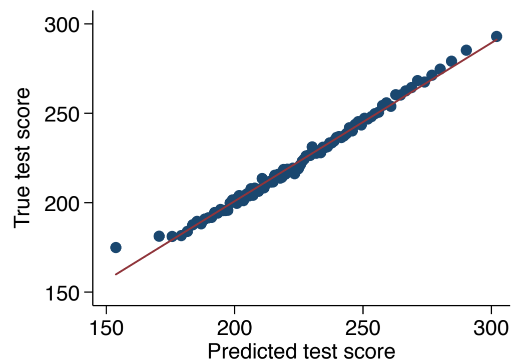
(b) Language

Notes: This figure presents the distribution of R-squared for all regressions of test scores on observable variables (i.e. predictors) among test takers in each school in our data. We include predictors linearly (solid line) or as a polynomial (dash line). Recall that these predictions include GPA, indicators for school switchers and students who are repeating the grade, and year fixed effects. Vertical lines denote the average R-square in the corresponding panel. Panel (a) plots the R-squared for the math test and panel (b) plots the R-squared for the language test. There are a total of 7,493 regressions in each panel.

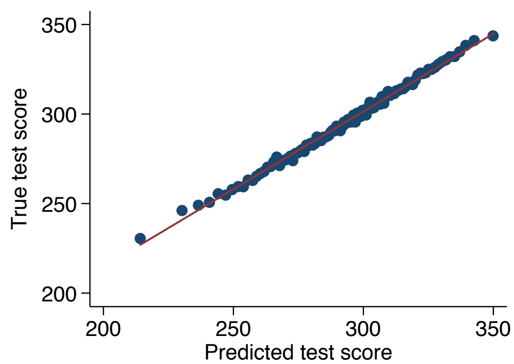
Figure A.11: Evaluation of prediction model



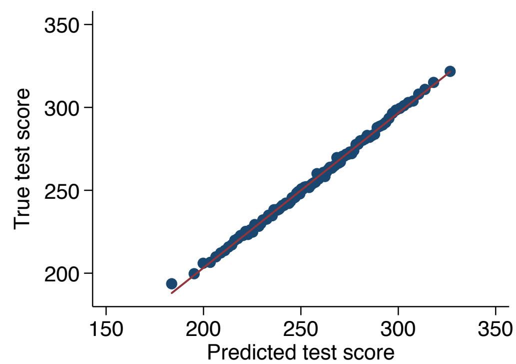
(a) All students



(b) Students with low academic performance



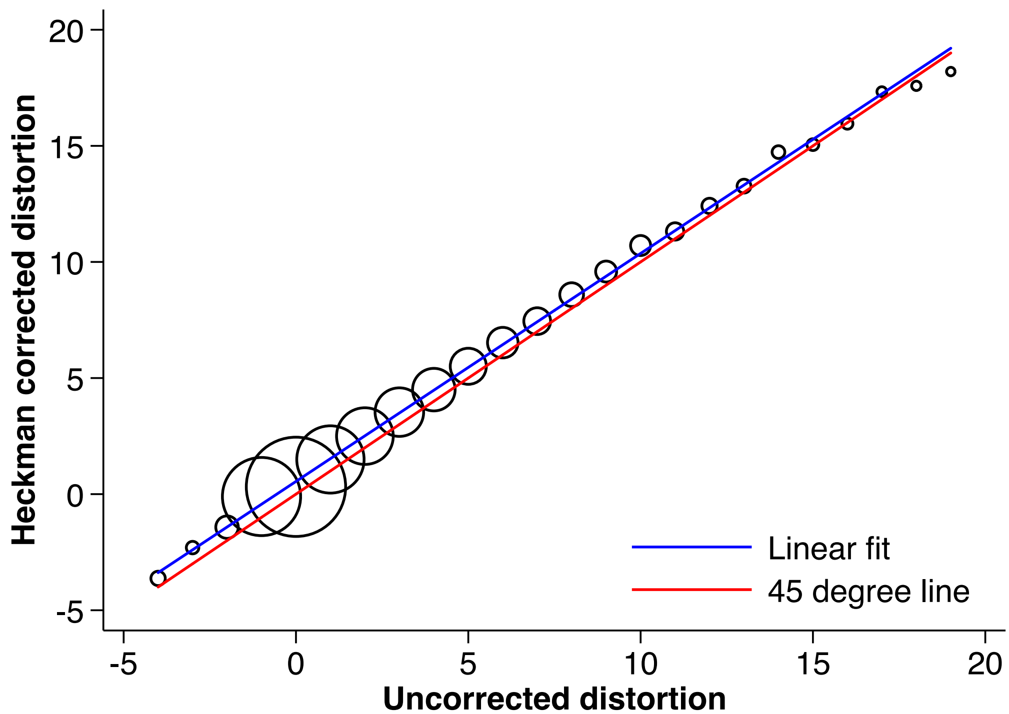
(c) Students with high academic performance



(d) Students with average academic performance

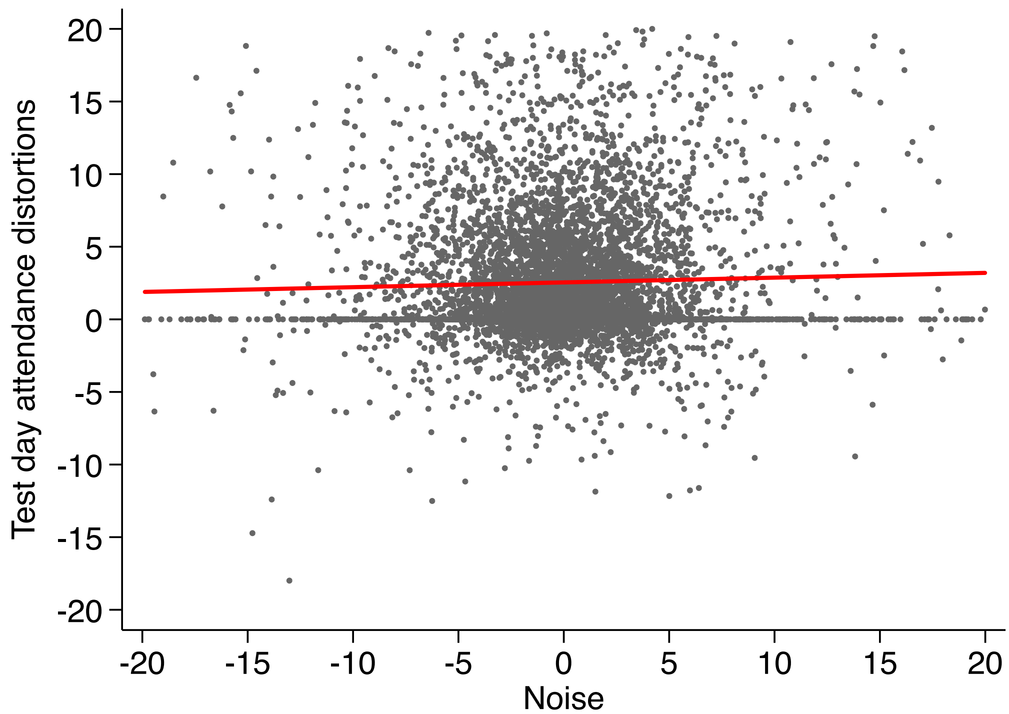
Notes: These figures present binscatter plots of "true test scores" (y-axis) and "predicted test scores" (x-axis) for different types of students. "True test scores" are observed test scores and "predicted test scores" were calculated using predetermined observable variables as predictors, combined using the estimated model in section 4 of the paper (equation 3). In these prediction exercises, we use the universe of test-takers – 1,929,654 students in the period 2005-2013 – and we delete 10% of observations in each school-year. Then, we proceed to predict test scores of the observations we deleted using the remaining 90% of students. This method allows us to evaluate the quality of our prediction. Students with low (high) academic performance are those below (above) the 25*th* (75*th*) percentile of the GPA distribution within a school-year.

Figure A.12: Heckman corrected distortions



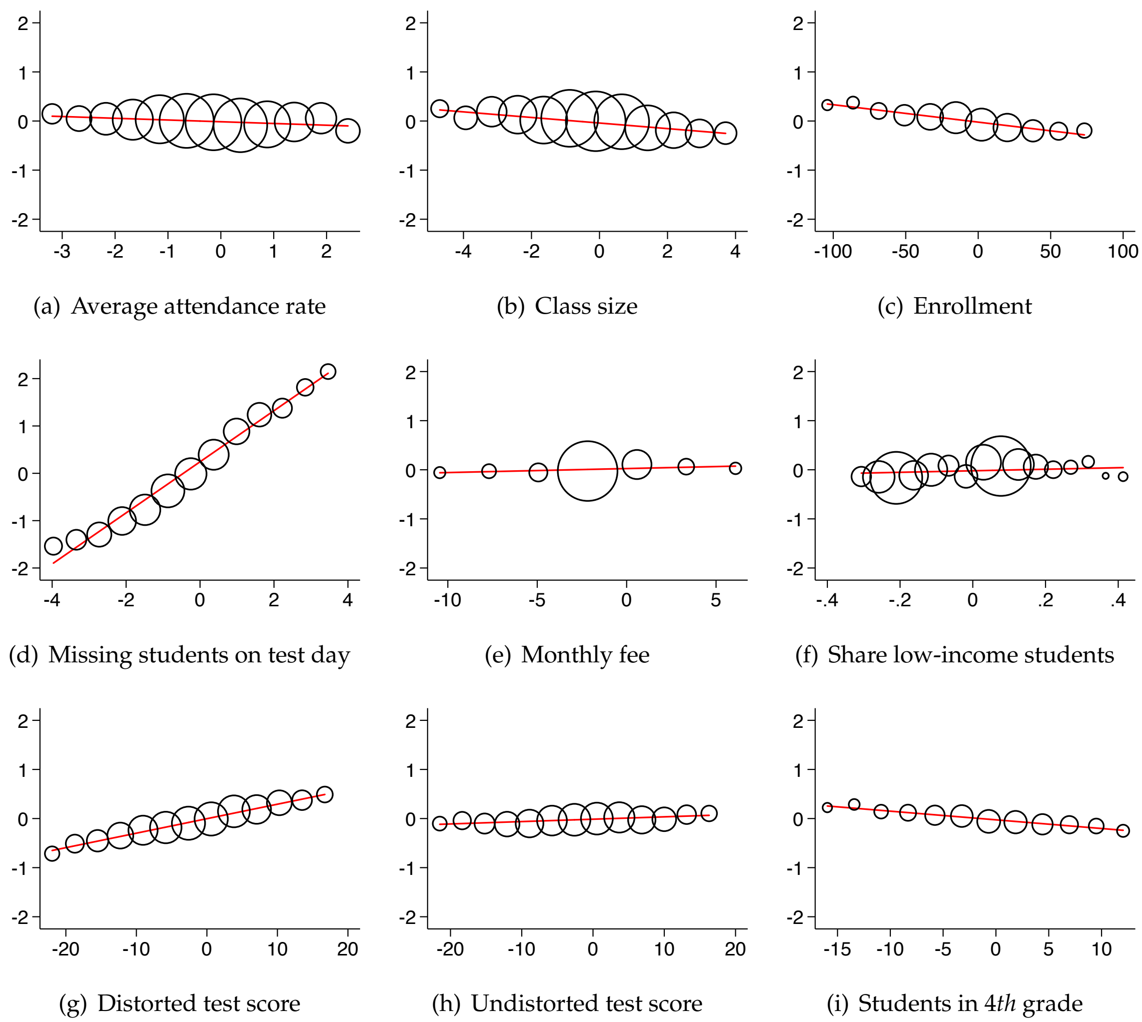
Notes: The excluded variable when calculating the Heckman corrected distortions is an indicator variable that takes the value of one for students that live outside of the municipality of the school.

Figure A.13: Distortions and noise



Notes: We construct a noise distribution for each school in our data using administrative estimates of noise in student-level test scores. These estimates are called "individual-level variability in test scores" and can be aggregated to construct measures of school-level noise following the method in Quality Education Agency (2013). This figure corresponds to a scatter plot showing the correlation between noise and distortions across schools as a linear fit. Each dot represents a school. The low correlation of 0.02 highlights that noise is mean independent of distortions. We conclude from this exercise that test day attendance represents a different (behavioral, non-statistical) margin that distorts quality signals.

Figure A.14: Distortions and school attributes



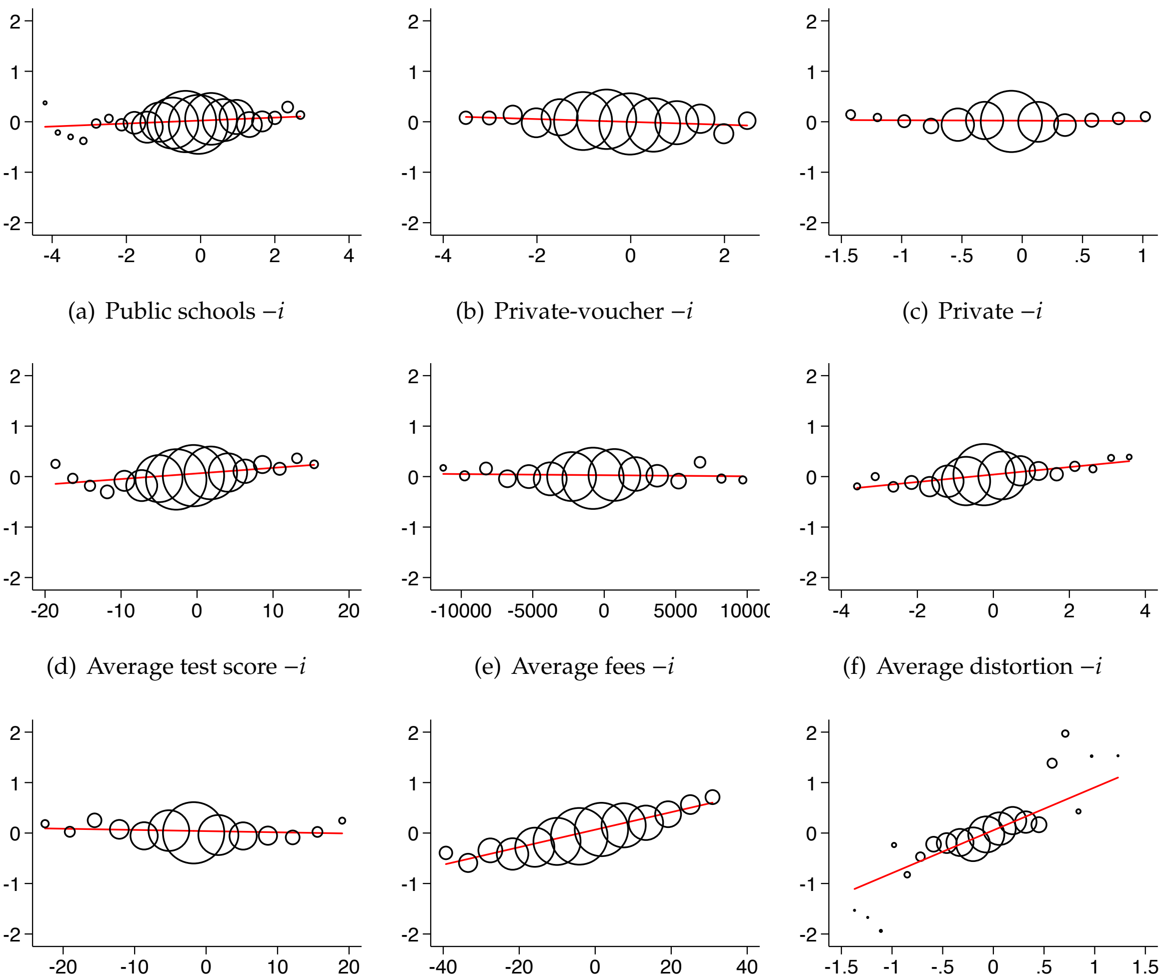
(a) Average attendance rate (b) Class size (c) Enrollment

(d) Missing students on test day (e) Monthly fee (f) Share low-income students

(g) Distorted test score (h) Undistorted test score (i) Students in 4*th* grade

Notes: These figures display the relationship between relevant school characteristics and distortions in quality signals. All variables have been residualized with school and year fixed effects. The size of markers indicates the number of students in it. The mean of distortion (y-axis) is 2.7 test score points.

Figure A.15: Distortions and attributes of schools within 3km



(a) Public schools $-i$ (b) Private-voucher $-i$ (c) Private $-i$

(d) Average test score $-i$ (e) Average fees $-i$ (f) Average distortion $-i$

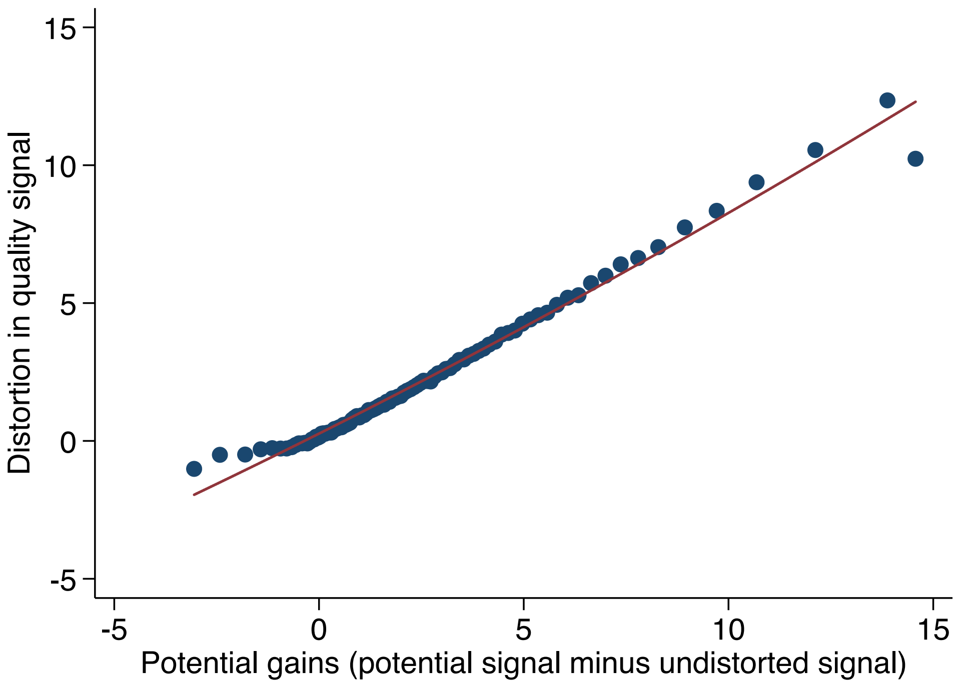
(g) Perc. fees i (h) Perc. test score i (i) Quality demand elasticity i

Notes: These figures display the relationship between relevant market characteristics and distortions in quality signals. All variables have been residualized with school and year fixed effects. The size of markers indicates the number of students in it. The mean of distortion (y-axis) is 2.7 test score points. Variables in panels (a) through (f) correspond to market aggregates excluding the reference school. Quality demand elasticities in panel (i) are calculated using the sample and estimates from the school choice model in section 5, as:

$$\eta^{q}_{jmt} = \frac{\partial s_{jmt}}{\partial q_{jmt}} \frac{q_{jmt}}{s_{jmt}} = \left(\sum_{r} \pi^{r}_{mt} \frac{1}{N^{r}_{mt}} \sum_{i \in \mathcal{I}^{r}_{mt}} \frac{\partial P^{r}_{ijmt}(d^{r}, \hat{\delta}^{r}, \hat{\beta}^{r}_{d})}{\partial q_{jmt}} \right) \frac{q_{jmt}}{s_{jmt}}$$

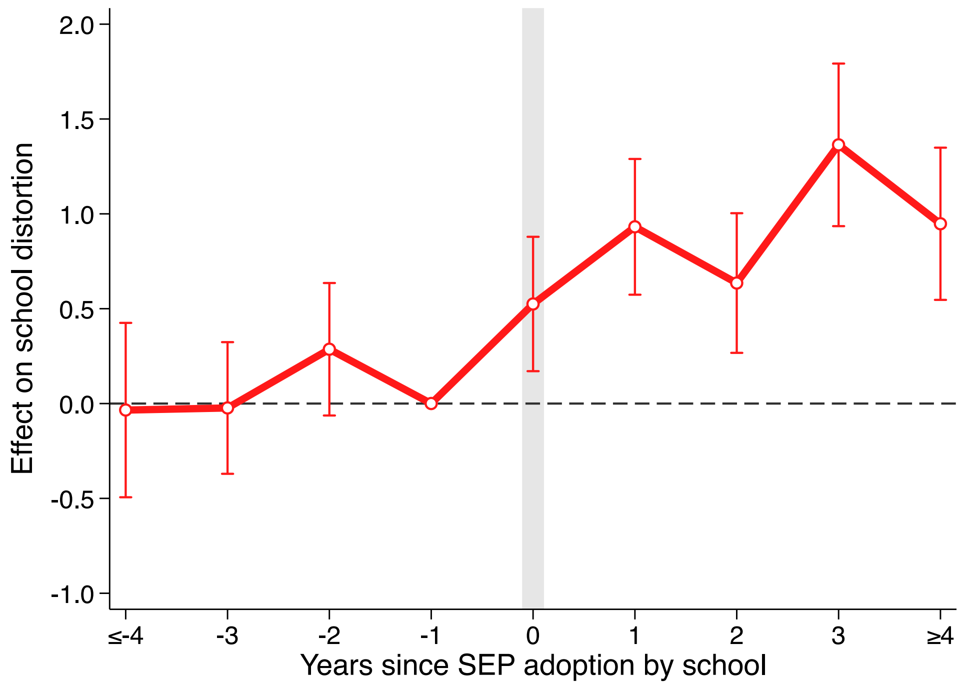
where π^{r}_{mt} is the share of households of type r in market m and year t, while N^{r}_{mt} and $\mathcal{I}^{r}_{mt}$ are the number and the set of such households respectively. The expression in brackets is thus simply a type-share-weighted average of the partial derivative of choice probabilities for school j with respect to quality. In the plot, both variables are residualized by removing school and year fixed effects.

Figure A.16: Potential gains and distortions



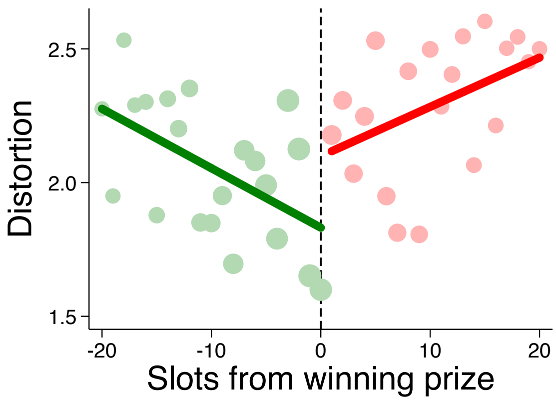
Notes: This figure displays a binned scatter plots of distortions on potential gains from having students not attend on test days. We compute potential gains as the difference between the average predicted school test score if the bottom 10 percent of the student GPA performance distribution does not take the test and the average predicted school test score if all students in the class take the test. The latter is what we call schools' undistorted quality signals. Both variables have been residualized with school and year fixed effects.

Figure A.17: Change in distortions around adoption of SEP program

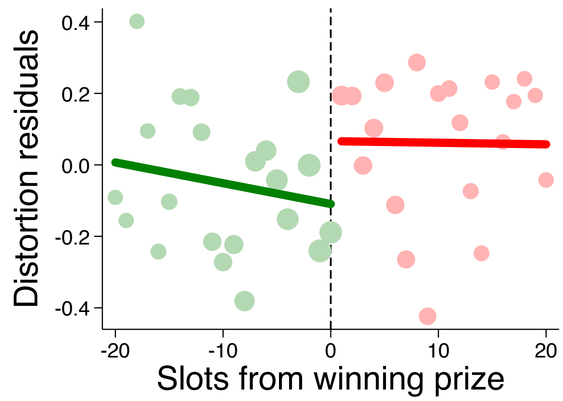


Notes: Event study analysis in equation (12) to test for the effect of affiliation to the SEP vouchers program on distortions in quality signals (y-axis). The x-axis displays years since a school adopts to the SEP program. Dots indicate coefficients for the effect of each year around the event on distortions in quality signals. The coefficient on the year before SEP adoption is normalized to zero. Clustered standard errors at the school level are displayed in brackets. We find that distortions in quality signals increase after SEP adoption.

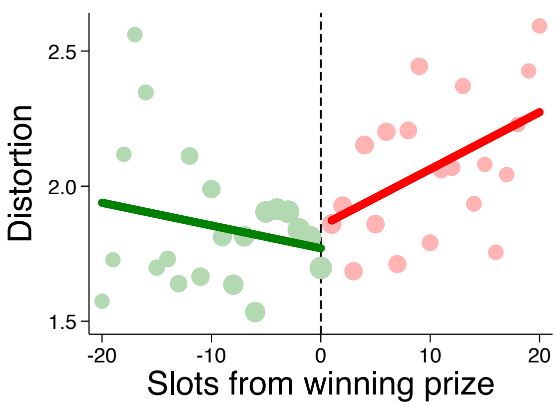
Figure A.18: Monetary incentives for teachers



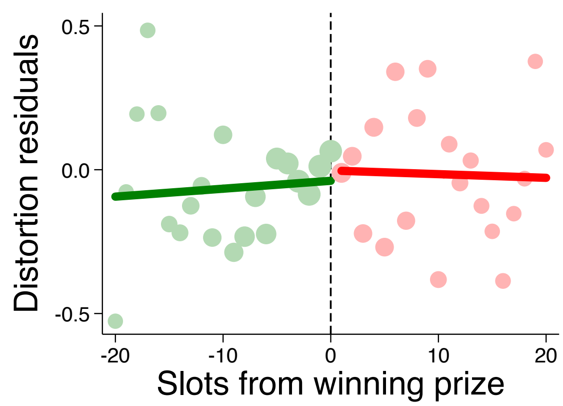
(a) Distortion in year $t + 1$



(b) Distortion in year $t + 1$



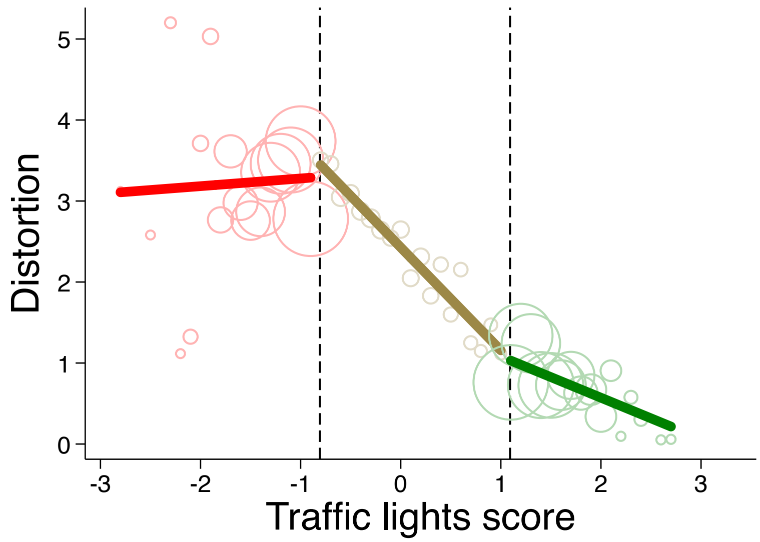
(c) Distortion in year $t + 2$



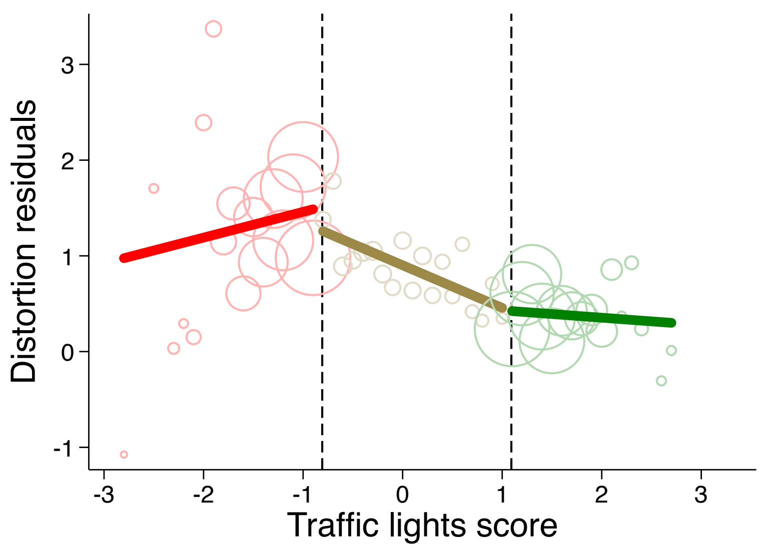
(d) Distortion in year $t + 2$

Notes: Regression kink design in equation (13) to test for the effect of monetary teacher incentives on distortions in quality signals (y-axis). The x-axis represents a measure of the probability of winning the prize (i.e. teacher bonuses). Schools to the left (right) of the thresholds won (did not win) the prize in the previous tournament. We present more details about this public program in section 2 of the paper. Left panels correspond to changes in the slope without controls while right panels control for a set of school fixed effects. The null hypothesis of incentives affecting distortions implies an "inverted V" relationship between "slots from winning prize" and distortions around the kink. We reject the hypothesis that teacher incentives cause distortions in quality signals.

Figure A.19: "Educational Traffic lights" policy



(a) Distortion in year 2010



(b) Distortion in year 2010

Notes: Regression kink design in equation (14) to test for the hypothesis of manipulation of test scores to be classified in a "higher" category. The x-axis represents school scores which fully determines their category. We present more details about the policy in section 2 of the paper. The null hypothesis of manipulation implies an "inverted V" relationship between school scores and distortions in quality signals. The upper panel corresponds to the test without controls while the lower panel controls for a basic set of pre-determined school characteristics. We strongly reject the hypothesis of manipulation of test scores for the school to be classified in a higher category.

Table A.1: Descriptive statistics for distortions by subject

	Obs.	Mean	St. Dev.	Min	Max	Years
Math	60,741	2.7	4.4	-3.5	23.9	2005–2013
Language	60,760	2.6	4.4	-3.4	23.8	2005–2013
Natural sciences	5,902	2.1	3.9	-7.8	20.6	2008, 2010
Social sciences	10,033	2.1	3.2	-3.5	17.0	2009

Notes: Distortions are measured in test score points and we estimated them using the methodology described in section 4.

Table A.2: School markets as connected components

	3km	4km	5km	6km	7km	8km	9km	10km
Markets	451	413	380	348	322	295	273	251
Markets with more than 1 schools	262	248	233	219	208	196	191	181
Markets with more than 5 schools	106	104	99	93	90	88	86	86
Markets with more than 10 schools	63	63	60	55	52	49	48	50
Markets with more than 20 schools	36	36	33	31	30	29	28	29

Notes: Let **A** be a $N \times N$ matrix representing the network of N =5,416 urban schools in Chile in the period 2005–2013. In network theory, **A** is referred to as adjacency matrix. This adjacency matrix represents an undirected network, i.e., **A** is a symmetric matrix. The element $A(i, j)$ in this adjacency matrix takes the value of one if school i and j are closer than κ kilometers from each other and zero otherwise. A "component" or "connected component" of **A** is a sub-network in which any two schools are connected to each other through some other school, i.e., we can always find a "path" that connects any two pair of schools in the sub-network. A market is defined as a connected component of **A**. In the paper, we use $\kappa = 5$ (highlighted in gray), but results are robust to different definitions.

Table A.3: IV results from the second stage of school choice model - First stage for school fees

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All			Low-income students			High-income students		
Rivals' characteristics									
Religious	-19.876**	79.768*	100.580	-11.500	68.481	11.209	-26.668**	85.263	195.296*
	(7.810)	(46.975)	(70.650)	(10.365)	(57.551)	(79.821)	(11.316)	(71.460)	(108.364)
Gender constraint	-80.777***	463.861***	780.010***	-90.315***	513.487***	617.324**	-62.196**	418.205**	922.088***
	(19.195)	(121.244)	(222.163)	(24.978)	(149.890)	(257.538)	(28.246)	(182.350)	(335.240)
Public	-17.294***	233.888***	-83.801	-9.406	-114.488**	-75.163	-21.657**	614.363***	-68.761
	(6.075)	(45.861)	(61.668)	(7.921)	(48.773)	(70.400)	(9.017)	(74.814)	(94.836)
Teacher wages									
Average hourly wage	0.094***	0.123***	0.135***	0.060	0.078*	0.089**	0.131***	0.170***	0.184***
	(0.031)	(0.032)	(0.030)	(0.042)	(0.043)	(0.041)	(0.045)	(0.047)	(0.045)
Voucher									
Baseline	-1.335***	-1.473***	-1.454***	-0.975***	-1.177***	-1.166***	-1.535***	-1.627***	-1.603***
	(0.031)	(0.030)	(0.029)	(0.059)	(0.055)	(0.054)	(0.037)	(0.036)	(0.035)
SEP school	0.062*	-0.080**	0.007	-0.093***	-0.217***	-0.077**	0.210***	0.056	0.090*
	(0.032)	(0.033)	(0.032)	(0.034)	(0.035)	(0.033)	(0.052)	(0.052)	(0.049)
SEP share	-10.034***	-9.616***	-1.556***	-9.927***	-9.825***	-0.856	-10.113***	-9.368***	-2.342***
	(0.185)	(0.187)	(0.546)	(0.235)	(0.241)	(0.636)	(0.279)	(0.279)	(0.815)
Temperature									
Linear	4.167***	2.684	0.621	3.980**	3.871	0.808	4.284**	0.709	-0.311
	(1.308)	(4.491)	(4.381)	(1.778)	(6.120)	(5.784)	(1.874)	(6.490)	(6.466)
Quadratic	-0.261***	-0.163	-0.095	-0.256***	-0.214	-0.110	-0.260***	-0.088	-0.058
	(0.054)	(0.179)	(0.174)	(0.074)	(0.243)	(0.230)	(0.078)	(0.259)	(0.258)
SNED program									
Prize residual	-5.773***	-4.227***	-5.363***	-3.588**	-2.150	-3.406**	-7.605***	-5.997***	-7.023***
	(1.211)	(1.159)	(1.143)	(1.560)	(1.499)	(1.472)	(1.816)	(1.727)	(1.698)
Controls	No	No	Yes	No	No	Yes	No	No	Yes
Market-Year F.E.	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	10,774	10,774	10,774	5,335	5,335	5,335	5,439	5,439	5,439
R-squared	0.685	0.729	0.739	0.665	0.716	0.730	0.706	0.748	0.758

Notes: All regressions are weighted by school enrollment. Columns 3, 6 and 9 include other school attributes in the corresponding second stage specifications, namely indicators for schools being religious, public, gender constrained or part of the SEP program. Results not reported in this table. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4: IV results from the second stage of school choice model - First stage for school quality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All			Low-income students			High-income students		
Rivals' characteristics									
Religious	1.173	12.207	62.650**	2.547	9.472	54.491	-0.046	14.997	71.121*
	(3.687)	(20.849)	(29.730)	(5.269)	(29.957)	(42.769)	(5.157)	(29.337)	(41.727)
Gender constraint	-42.162***	-26.845	375.535***	-45.462***	-27.096	372.044***	-38.185***	-26.725	377.581***
	(8.451)	(46.254)	(77.523)	(12.077)	(65.914)	(110.647)	(11.852)	(65.569)	(109.687)
Public	-7.425***	322.369***	-34.034	-6.927*	321.522***	-46.263	-7.653**	324.807***	-20.461
	(2.729)	(22.419)	(30.724)	(3.881)	(32.046)	(43.895)	(3.834)	(31.777)	(43.497)
Teacher wages									
Average hourly wage	0.060***	0.064***	0.072***	0.059***	0.062***	0.071***	0.061***	0.067***	0.074***
	(0.013)	(0.014)	(0.013)	(0.018)	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)
Voucher									
Baseline	-0.212***	-0.247***	-0.234***	-0.183***	-0.231***	-0.219***	-0.227***	-0.254***	-0.241***
	(0.009)	(0.009)	(0.009)	(0.016)	(0.016)	(0.015)	(0.012)	(0.012)	(0.011)
SEP school	0.715***	0.604***	0.625***	0.720***	0.615***	0.636***	0.709***	0.593***	0.614***
	(0.018)	(0.017)	(0.017)	(0.025)	(0.024)	(0.024)	(0.025)	(0.025)	(0.024)
SEP share	-4.663***	-4.149***	-0.157	-4.694***	-4.200***	-0.177	-4.628***	-4.092***	-0.134
	(0.082)	(0.079)	(0.202)	(0.115)	(0.113)	(0.289)	(0.117)	(0.113)	(0.286)
Temperature									
Linear	4.151***	1.492	0.620	4.134***	1.727	0.620	4.166***	1.196	0.554
	(0.494)	(1.630)	(1.489)	(0.712)	(2.339)	(2.115)	(0.686)	(2.298)	(2.122)
Quadratic	-0.208***	-0.091	-0.064	-0.206***	-0.105	-0.067	-0.209***	-0.076	-0.059
	(0.021)	(0.066)	(0.060)	(0.030)	(0.094)	(0.085)	(0.029)	(0.093)	(0.085)
SNED program									
Prize residual	1.713***	3.029***	2.412***	1.861***	3.143***	2.492***	1.598**	2.935***	2.349***
	(0.486)	(0.447)	(0.431)	(0.687)	(0.636)	(0.614)	(0.689)	(0.634)	(0.612)
Controls	No	No	Yes	No	No	Yes	No	No	Yes
Market-Year F.E.	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	10,774	10,774	10,774	5,335	5,335	5,335	5,439	5,439	5,439
R-squared	0.391	0.474	0.512	0.367	0.452	0.492	0.412	0.493	0.529

Notes: All regressions are weighted by school enrollment. Columns 3, 6 and 9 include other school attributes in the corresponding second stage specifications, namely indicators for schools being religious, public, gender constrained or part of the SEP program. Results not reported in this table. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: OLS results from the second stage of school choice model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All sample			Low-income students			High-income students		
Fee	-0.004***	-0.004***	-0.003***	-0.009***	-0.010***	-0.009***	-0.002***	-0.001***	-0.003***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Quality	0.010***	0.011***	0.011***	0.003***	0.005***	0.006***	0.017***	0.017***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Religious			-0.040*			-0.074**			0.000
			(0.023)			(0.029)			(0.028)
Gender constraint			0.233***			0.237***			0.222***
			(0.043)			(0.053)			(0.050)
Public			0.039			0.126***			-0.049
			(0.026)			(0.032)			(0.033)
SEP school			0.012			0.028			-0.247***
			(0.042)			(0.054)			(0.045)
Market-Year F.E.	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	11,041	11,041	11,041	5,461	5,461	5,461	5,580	5,580	5,580
R-squared	0.025	0.370	0.373	0.072	0.488	0.494	0.080	0.561	0.567

Notes: All regressions are weighted by school enrollment. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.6: Understanding distortions

Dependent variable: distortions in quality signals (in test score points)

	All		Distortions> 0	
A – School attributes	(1)	(2)	(3)	(4)
Public	1.41***	1.26***	0.65**	0.54
	(0.13)	(0.14)	(0.31)	(0.33)
Religious	0.03	-0.11	0.18	0.03
	(0.08)	(0.08)	(0.17)	(0.20)
For-profit	0.35***	0.40***	0.91***	0.94***
	(0.11)	(0.11)	(0.31)	(0.32)
Log parents income	-0.65***	-0.60***	-0.71***	-0.79***
	(0.04)	(0.05)	(0.10)	(0.13)
Average annual attendance	-0.08*	-0.19***	-0.20**	-0.29**
	(0.04)	(0.05)	(0.10)	(0.12)
Students in 4*th* grade	-0.17	-0.11	-2.37***	-2.21***
	(0.15)	(0.15)	(0.25)	(0.26)
Enrollment in grades 1*st*-8*th*	-0.43***	-0.52***	0.04	0.14
	(0.16)	(0.16)	(0.25)	(0.26)
Indicator SEP	1.12***	0.59***	1.42***	0.62*
	(0.07)	(0.10)	(0.15)	(0.35)
Constant	1.22***	1.64***	5.35***	5.97***
	(0.13)	(0.14)	(0.31)	(0.39)
B – Autocorrelation				
Lagged distortion	0.41***	0.38***	0.39***	0.37***
	(0.01)	(0.02)	(0.03)	(0.03)
Constant	1.97***	2.06***	6.25***	6.30***
	(0.04)	(0.05)	(0.13)	(0.14)
Mean of dep. variable	2.18	2.18	5.11	5.11
Market-year F.E.	No	Yes	No	Yes
Variance explained by schools F.E.	0.36	0.36	0.60	0.60
F-test school F.E.	4.59	4.59	2.96	2.96
Schools	3,417	3,417	2,339	2,339
Observations	29,588	29,579	5,929	5,927

Notes: Estimation includes all urban schools. All non-indicator variables have been normalized (except for lagged distortion). All regressions are weighted by the inverse of the uncertainty associated to the calculation of distortions, where uncertainty is the size of the confidence interval. Columns 3-4 restrict the data to school-year observations with distortions statistically different from zero. Robust standard errors in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.