Parent-Child Information Frictions and Human Capital Investment: Evidence from a Field Experiment*

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This paper uses a field experiment to answer how information frictions between parents and their children affect human capital investment and how much reducing these frictions can improve student achievement. In Los Angeles, a random sample of parents was provided detailed information about their child's academic progress. As in a standard principal-agent model, more information allowed parents to induce more effort from their children, which translated into gains in achievement. However, additional information also changed parents' beliefs and spurred demand for information from the school. Relative to other interventions, additional information to parents potentially produces gains in achievement at a low cost.

JEL Codes: I20, I21, I24.

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I Introduction

Numerous papers reinforce the importance of parental investments in their child's human capital, and in turn, long-term economic outcomes (e.g. Cunha et al., 2006; Houtenville and Smith Conway, 2007; Todd and Wolpin, 2007). However, if children hide school-related information from their parents, a principal-agent problem might arise that impedes these investments. This paper uses a field experiment to answer how information frictions impede parental investments and if reducing these frictions can improve student effort and achievement.

At the outset it is uncertain whether additional information to parents can improve outcomes. There is an association between the quality of information schools provide and school performance: In schools where most students go on to college, 83% of parents are satisfied with the school's ability to communicate information about their child's academic performance, but in schools where most students do not go on to college, 43% of the parents are satisfied with this communication (Civic Enterprises, 2004). However it is not clear what underlies this association. Parents of students who are performing well might be receiving better information or they might require less information because their children have greater academic ability. Even if more information does increase parental investment in their child's education, it is not obvious this will improve academic outcomes. More information might help parents induce more effort from their children, but complementary inputs of the education production function, such as teacher instruction, also determine if this effort translates into measurable gains in achievement.

To measure the causal effect of additional information on parents' investments in their children and student outcomes, I conducted an experiment at a low-performing school near downtown Los Angeles. Out of all 462 students in grades six through eleven, 242 students' parents or guardians were randomly selected to receive additional information about their child's academic progress. This information consisted of emails, text messages and phone calls listing students' missing assignments and grades several times a month over a six-month period. The information provided was detailed. Messages contained the class, assignment names, problems and page numbers of the missing work whenever possible. Course grades were sent to families every five to eight weeks.[1] To quantify the effects on student effort, achievement and parental investments, I gathered administrative data on assignment completion, work habits, cooperation, attendance and test scores. Parent and student surveys were conducted immediately after the school year ended to provide additional data about each family's response.

[1]This is in addition to the report cards sent by mail to all families in the treatment and control groups.

The results for high school students suggest there are significant information frictions between parents and their children. As in a standard principal-agent model, more information increased the intensity of parents' incentives and improved their child's effort. Importantly however, some parents were not fully aware of these frictions. Parents in the high school treatment group were twice as likely as the control group to believe that their child does not tell them enough about their schoolwork and grades. This change in beliefs coincides with an increase in parents' demand for information from the school about their child's academic progress. Parents in the treatment group contacted the school about this information 83% more often than the control group, and parent-teacher conference attendance increased by 53%. Unfortunately, the middle-school teachers replicated the treatment for all students in their grades, contaminating the results for those families. There was no estimated effect on middle school parent or student outcomes.

In terms of achievement, reducing these information problems can potentially produce gains on par with education reforms such as high-quality charter schools. For high school students, GPA increased by .19 standard deviations. There is evidence that test scores for math increased by .21 standard deviations, though there was no gain for English scores (.04 standard deviations). These effects are driven by a 25% increase in assignment completion and a 24% and 25% decrease in the likelihood of unsatisfactory work habits and cooperation, respectively. Classes missed by students decreased by 28%. For comparison, the Harlem Children's Zone increased math scores and English scores by .23 and .05 standard deviations and KIPP Lynn charter schools increased these scores .35 and .12 standard deviations (Dobbie and Fryer, 2010; Angrist et al., 2010).

Relative to other interventions, providing information could be a cost effective way to address sub-optimal student effort and reduce the achievement gap.[2] Interventions aimed at adolescents' achievement are often costly because they rely on financial incentives, either for teachers (Springer et al., 2010; Fryer, 2011), for students (Angrist and Lavy, 2002; Bettinger, 2008; Fryer, 2011) or for parents (Miller, Riccio and Smith, 2010). Providing financial incentives for high school students cost $538 per .10 standard-deviation increase, excluding administrative costs (Fryer, 2011). If teachers were to provide additional information to parents as in this study, the cost per student per .10 standard-deviation increase in GPA or math scores would be $156 per child per year. Automated messages could reduce this cost further.

These costs raise an important related question, which is how much parents might be

[2]Examples of other information-based interventions in education include providing families information describing student achievement at surrounding schools (Hastings and Weinstein, 2008; Andrabi, Das and Khwaja 2009), parent outreach programs (Avvisati et al., 2010), providing principals information on teacher effectiveness (Rockoff et al., 2010) and helping parents fill out financial aid forms (Bettinger et al., 2009).

willing to pay to reduce these information problems. This study does not address this question, but Bursztyn and Coffman (2011) use a lab experiment with low-income families in Brazil to show parents are willing to pay substantial amounts of money for information on their child's attendance.

While this paper shows that an intensive information-to-parents service potentially can produce gains to student effort and achievement, its policy relevance depends on how well it translates to other contexts and scales up. Large school districts such as Los Angeles, Chicago, and San Diego have purchased systems that make it easier for teachers to improve communication with parents by posting grades online, sending automated emails regarding grades, or text messaging parents regarding schoolwork. The availability of these services prompts questions about their usage, whether teachers update their grade books often enough to provide information, and parental demand for this information. This paper discusses but does not address these questions empirically.

The rest of the paper proceeds as follows. Section II outlines a basic framework to interpret the empirical analysis. Sections III and IV describe the experimental design and the estimation strategy. Sections V and VI present the results for the high school students and middle school students, respectively. Section VII concludes with a discussion of external validity and cost-effectiveness.

II Framework

Typically, models of human capital investment do not incorporate information frictions between parents and their children.[3] Students may wish to hide information from their parents about their human capital investment due to higher discount rates or difficulty planning for the future (Bettinger and Slonim, 2007; Steinberg et al., 2009; Levitt, List, Neckermann and Sadoff, 2011).

The framework below posits a simple non-cooperative interaction between parents and their children to show how additional information can affect student achievement. Student achievement A is a function of student effort e and teacher quality T. Effort e is also a function of a vector z and a vector of parental investments I. z includes a student's ability, peers, discount rate, and value of education. A child takes I as given and maximizes $\max_e \{u(A(e; I, z, T)) - e\}$. Solving, the best response to I is $e(I, z, T)$.

Parents choose I at a cost of $c(I; \varepsilon, t)$. The cost function represents summarizes the cost of parental monitoring, helping with schoolwork directly, or providing incentives. The

[3]Several important exceptions in the context of human-capital investment are Weinberg (2001), Berry (2009), and Bursztyn and Coffman (2011).

vector ε captures parental heterogeneity such as their value of education, work schedule, and parenting skills. t is an indicator variable for receiving the information treatment. Parents take their child's best response as given and maximize the utility they get from their achievement (normalized to A): $A(e(I;z,T)) - c(I;\varepsilon,t)$. The first-order condition yields

$$\frac{\partial A(e(I;z,T))}{\partial e} \times \frac{\partial e(I;z,T)}{\partial I} = \frac{\partial c(I;\varepsilon,t)}{\partial I} \tag{1}$$

The right-hand side of equation (1) is the marginal cost of parents' investments. The information treatment t could reduce this marginal cost, for instance, by lowering monitoring costs for parents. In a standard moral hazard problem, this lower monitoring cost could increase the intensity of incentives, and in turn, improve student effort. I examine this implication using survey and administrative data.

Equation (1) also highlights several complementarities. The treatment effect depends on parents' valuation of education (part of ε). Parents who place little value on education are likely to ignore information regarding their child's academic progress. Even if the implication of the standard principal-agent model holds such that investment increases and student effort increases ($\partial e(I;z,T)/\partial I > 0$), this does not imply a positive effect on student achievement, which depends on the quality of teacher inputs T in the achievement function. If teachers provide students work that is either unproductive or that does not translate into higher test scores, then there will be no measured effect on achievement. The effect size of additional information on investments and achievement is uncertain *ex ante*.

III Background and Experimental Design

A Background

The experiment took place at a K-12 school during the 2010-2011 school year. This school is part of Los Angeles Unified School District (LAUSD), which is the second largest district in the United States. The district has graduation rates similar to other large urban areas and is low performing according to its own proficiency standards: 55% of LAUSD students graduate high school within four years, 25% of students graduate with the minimum requirements to attend California's public colleges, 37% of students are proficient in English-Language Arts and 17% are proficient in math.[4]

The school is in a low-income area with a high percentage of minority students. 90% of students receive free or reduced-price lunch, 74% are Hispanic and 21% are Asian. Compared to the average district scores above, the school performs less well on math and English state

[4]This information and school-level report cards can be found online at http://getreportcard.lausd.net/reportcards/reports.jsp.

exams; 8% and 27% scored proficient or better in math and English respectively. 68% of teachers at the school are highly qualified, which is defined as being fully accredited and demonstrating subject-area competence.[5] In LAUSD, the average high school is 73% Hispanic, 4% Asian and 89% of teachers are highly qualified.[6]

The school context has several features that are distinct from a typical LAUSD school. The school is located in a large building complex designed to house six schools and to serve 4,000 students living within a nine block radius. These schools are all new, and grades K-5 opened in 2009. The following year, grades six through eleven opened. Thus in the 2010-2011 school year the sixth graders had attended the school in the previous year while students in grades seven and above spent their previous year at different schools. Families living within the nine-block radius were designated to attend one of the six new schools but were allowed to rank their preferences for each. These schools are all pilot schools, which implies they have greater autonomy over their budget allocation, staffing, and curriculum than the typical district school.[7]

B Experimental Design

The sample frame consisted of all 462 students in grades six through eleven enrolled at the school in December of 2010. Of those, 242 students' families were randomly selected to receive the additional information treatment. This sample was stratified along indicators for being in high school, having had a least one D or F on their mid-semester grades, having a teacher think the service would helpful for that student, and having a valid phone number.[8] Students were not informed of their family's treatment status nor were they told that the treatment was being introduced. Teachers knew about the experiment but were not told which families received the additional information. Interviews with students suggest that students discussed the messages with each other. It is possible that students in the treatment group and teachers could infer who was regularly receiving messages and who was not as time went on.

The focus of the information treatment was missing assignments, which included homework, classwork, projects, essays and missing exams. Each message contained the assignment name or exam date and the class it was for whenever possible. For some classes, this name

[5] Several papers have shown that observable teacher characteristics are uncorrelated with a teacher's effect on test scores (Aaronson et al., 2008; Jacob and Lefgren, 2008; Rivken et al., 2005). Buddin (2010) shows this result applies to LAUSD as well.

[6] This information is drawn from the district-level report card mentioned in the footnote above.

[7] The smaller pilot school system in Los Angeles is similar to the system in Boston. Abdulkadiroglu et al. (2011) find that the effects of pilot schools on standardized test scores in Boston are generally small and not significantly different from traditional Boston public schools. For more information on LAUSD pilot schools, see http://publicschoolchoice.lausd.net/sites/default/files/Los%20Angeles%20Pilot%20Schools%20Agreement%20%28Signed%29.pdf.

[8] The validity of the phone number was determined by the school's automated-caller records.

included page and problem numbers; for other classes it was the title of a project, worksheet or science lab. Overwhelmingly, the information provided to parents was negative—nearly all about work students did not do. The treatment rule was such that a single missing assignment in one class was sufficient to receive a message home about. All but one teacher accepted late work for at least partial credit. Parents also received current-grades information three times and a notification about upcoming final exams.

The information provided to parents came from teacher grade books gathered weekly from teachers. 14 teachers in the middle school and high school were asked to participate by sharing their grade books so that this information could be messaged to parents. The goal was to provide additional information to parents twice a month if students missed work. The primary constraint on provision was the frequency at which grade books were updated. Updated information about assignments could be gathered every two-to-four weeks from nine of the fourteen teachers. Therefore these nine teachers' courses were the source of information for the messages and the remaining teachers' courses could not be included in the treatment. These nine teachers were sufficient to have grade-book level information on every student.

The control group received the default amount of information the school provided. This included grade-related information from the school and from teachers. Following LAUSD policy, the school mailed home four report cards per semester. One of these reports was optional—teachers did not have to submit grades for the first report card of the semester. The report cards contained grades, a teacher's comment for each class, and each teacher's marks for cooperation and work habits. Parent-teacher conferences were held once a semester. Attendance for these conferences was very low for the high school (roughly 15% participation) but higher for the 7th and 8th grade (roughly 50%) and higher still for the 6th grade (100%). Teachers could also provide information to parents directly. At baseline, many teachers had not contacted any parents, and the median number of calls made to parents regarding their child's grades was one. No teacher had posted grades on the Internet though two teachers had posted assignments.

Figure 1 shows the timeline of the experiment and data collection. Baseline data was collected in December of 2010. That same month, contact numbers were culled from emergency cards, administrative data and the phone records of the school's automated-calling system. In January 2011, parents in the treatment group were called to inform them that the school was piloting an information service provided by a volunteer from the school for half the parents at the school. Parents were asked if they would like to participate, and all parents consented. These conversations included questions about language preference, preferred method of contact—phone call, text message or email—and parents' understanding of the A-F grading system. Most parents requested text messages (79%), followed by emails (13%) and phone calls (8%).[9]

The four mandatory grading periods after the treatment began are also shown, which includes first-semester grades. Before the last progress report in May, students took the California Standards Test (CST), which is a state-mandated test that all students are supposed to take.[10] Surveys of parents and students were conducted over the summer in July and August.

Notifications began in early January of 2011 and were sent to parents of middle school students and high school students on alternating weeks. This continued until the end of June, 2011. A bar graph above the timeline charts the frequency of contact with families over six months. The first gap in messages in mid February reflects the start of the new semester and another gap occurs in early April during spring vacation. This graph shows there was a high frequency of contact with families.

C Contamination

The most severe, documented form of contamination occurred when middle school teachers had a school employee replicate the treatment for all students, treatment and control. This employee called parents regarding missing assignments and set up parent-teacher conferences in addition to the school-wide conferences. This contamination began four-to-five weeks after the treatment started and makes interpreting the results for the middle school sample difficult.

For the high-school sample, a math teacher threatened his classes (treatment and control students) with a notification via the information treatment if they did not do their assignments. These sources of contamination likely bias the results toward zero.

Due to the degree of contamination in the middle school, I analyze the results for the stratified subgroups of middle school and high school students separately.

IV Data and Empirical Strategy

A Baseline Data

Baseline data include administrative records on student grades, courses, attendance, race, free-lunch status, English-language skills, language spoken at home, parents' education levels

[9] A voicemail message containing the assignment-related information was left if no one picked up the phone.
[10] Students with special needs can be exempted from this exam.

and contact information. There are two measures of GPA at baseline. For 82% of high school students, their cumulative GPA prior to entering the school is also available, but this variable is missing for the majority of middle school students. The second measure of GPA is calculated from their mid-semester report card, which was two months before the treatment began. At the time of randomization only mid-semester GPA was available. Report cards contain class-level grades and teacher-reported marks on students' work habits and cooperation. As stated above, there is an optional second-semester report card, however the data in this paper uses mandatory report cards to avoid issues of selective reporting of grades by teachers. Lastly, high school students were surveyed by the school during the first semester and were asked about whom they lived with and whether they have Internet access. 73% of students responded to the school's survey.

Teachers were surveyed about their contact with parents and which students they thought the information treatment would be helpful for. The latter is coded into an indicator for at least one teacher saying the treatment would be helpful for that student.

B Achievement-Related Outcomes

Achievement-related outcomes are students' grades, standardized test scores and final exam or project scores from courses. Course grades and GPA are drawn from administrative data on report cards. There are four mandatory report cards available after the treatment began, but only end-of-semester GPA and grades remain on a student's transcript. Final exam and project grades come from teacher grade books and are standardized by class.

The standardized test scores are scores from the California Standards Tests. These tests are high-stakes exams for schools but are low stakes for students. The math exam is subdivided by topic: geometry, algebra I, algebra II and a separate comprehensive exam for students who have completed these courses. The English test is different for each grade. Test scores are standardized to be mean zero and standard deviation one for each different test within the sample.

C Effort-Related Outcomes

Measures of student effort are student work habits, cooperation, attendance and assignment completion. Work habits and cooperation have three ordered outcomes: excellent, satisfactory and unsatisfactory. There is a mark for cooperation and work habits for each class and each grading period, and students typically take seven to eight classes per semester. Assignment completion is coded from the teacher grade books. Missing assignments are coded into indicators for missing or not.

There are three attendance outcomes. Full-day attendance rate is how often a child attended the majority of the school day. Days absent is a class-level measure showing how many days a child missed a particular class. The class attendance rate measure divides this number by the total days enrolled in a class.

D Parental Investments and Family Responses to Information

Telephone surveys were conducted to examine parent and student responses to the intervention not captured by administrative data. For parents, the survey asked about their communication with the school, how they motivated their child to get good grades, and their perceptions of information problems with their child about schoolwork. Parent-teacher conference attendance was obtained from the school's parent sign-in sheets. The student survey asked about their time use after school, their communication with their parents and their valuations of schooling.[11]

The parent and student surveys were conducted after the experiment ended by telephone. 52% of middle-school students' families and 61% of high-school students' families responded to the telephone survey.[12] These response rates are analyzed in further detail below.

To reduce potential social-desirability bias—respondents' desire to answer questions as they believe surveyors would want—the person who sent messages regarding missing assignments and grades did not conduct any surveys. No explicit mention about the information service was made until the very end of the survey.

E Attrition, Non Response, Missing CST Scores

Of the original of 462 students in the sample, 32 students left the school, 8% of whom were in the treatment group and 6% of whom were in the control group. The most frequent cause of attrition is transferring to a different school or moving away. Students who left the school are lower performing than the average student. The former have significantly lower baseline GPA and attendance as well as poorer work habits and cooperation. Table A.1 shows these correlates in further detail for middle school and high school students separately.

Just over one third of high-school parents did not respond to the survey.[13] Table A.2 shows nonresponse for families of high school students. Nonresponse is uncorrelated with treatment status for both children and parents. However, if those who did not respond differ

[11]Students were also asked to gauge how important graduating college and high school is to their parents, but there was very little variation in the responses across students so these questions are omitted from the analysis.

[12]The school issued a paper-based survey to parents at the start of the year and the response rate was under 15%. An employee of LAUSD stated that the response rates for their paper-based surveys is 30%.

[13]For comparison, LAUSD has said their non-response rate for parent surveys is roughly double this number.

from the typical family, then results based on the surveys may not be representative of the school population. This is true, as a regression of an indicator for non response on baseline characteristics shows the latter are jointly significant (results not shown). Nonetheless, the majority of families responded and provide insight into how they responded to the additional information.

Lastly, many students did not take the California Standards Test. 8% of scores are missing for math and 7% of scores are missing for English. These tests were taken on different days. Table A.3 in the appendix shows the correlates of missing scores for high school students. Baseline controls are added for each of the first three columns with an indicator for missing math scores as the dependent variable. The remaining three columns perform the same exercise for missing English scores. The treatment is negatively and significantly associated with missing scores. The potential bias caused by these missing scores is analyzed in the results section on test scores.

F Descriptive Statistics

In practice, the median treatment-group family was contacted 10 times over six months. Mostly mothers were contacted (62%), followed by fathers (24%) and other guardians or family members (14%). 60% of parents asked to be contacted in Spanish, 32% said English was acceptable, and 8% wanted Korean translation.

Figures 2 and 3 depict GPA and teacher-marked behavior distributions from the mandatory report card at baseline for all students.[14] For every report card, work habits and cooperation are graded as excellent, satisfactory or unsatisfactory for each student's class. Teachers describe the work habits grade as measuring how on task a student is while cooperation reflects how respectful their classroom behavior is. Figure 3 shows the majority of students receive satisfactory or excellent marks for class cooperation and only 10% of students receive an unsatisfactory mark. Work-habit grades are more uniformly distributed across the three possible marks.

Table 1 presents baseline-summary statistics across the treatment group and the control group for high school students. Panel A contains these statistics for the original sample while Panel B excludes attriters to show the balance of the sample used for estimations. Measures of works habits and cooperation are coded into indicators for unsatisfactory or not and excellent or not. Of the 13 measures, one difference—the fraction of female students—is significantly different (p-value of .078) between the treatment and control group in Panel A. All results are robust to adding gender as a control. Work habits and students' cumulative

[14]For high school students, 22% of students have a baseline GPA of 1.00 or below, while 19% of students have 3.00 or above.

GPA from their prior grades are better (but not significantly) for the control group than the treatment group. Panel B shows that baseline GPA is .06 points higher for the control group than the treatment group in the sample used for analysis, and as shown below, results are sensitive to this control. One concern with this baseline difference is mean reversion, however students' prior GPA, which is a cumulative measure of their GPA over several years, also shows the treatment group is lower achieving than the control group. In addition, GPA for the control group is highly persistent from the end of the first semester to the end of the second semester. A regression of the latter on the former yields a coefficient near one.[15]

G Empirical Strategy

The empirical analyses estimate intent-to-treat effects. Families in the treatment group may have received fewer or no notifications because their child has special needs (13 families); the guidance counselor requested them removed from the list due to family instability (two families); or the family speaks a language other than Spanish, English or Korean (two families). All of these families are included in the treatment group.

To measure the effect of additional information on various outcomes, I estimate the following

$$y_i = \alpha + \beta * Treatment_i + X_i'\gamma + \varepsilon_i \tag{2}$$

Control variables in X include baseline GPA and cumulative GPA from each student's prior school, grade indicators and strata indicators. The results are robust to various specifications so long as a baseline measure of GPA is controlled for, which most likely makes a difference due to the .06 point difference at baseline.

I estimate equation 2 with GPA as a dependent variable. To discern whether there were any differential effects by subject or for "targeted" classes—those classes for which a teacher shared a grade book in a timely fashion—I also use class grades as a dependent variable.[16] This regression uses the same controls as 2 above but the standard errors are clustered at the student level.[17] End-of-semester grades are coded on a four-point scale to match GPA calculations.[18]

Similar to class grades, there is a work habit mark and a cooperation mark for each

[15] Mean reversion does occur between students' prior GPA and their baseline GPA, however this reversion does not differ by treatment status (results available on request).

[16] Recall that only nine of the 14 teachers updated their grade books often enough so that assignment-related information could be provided to parents. The class-grades regression estimates whether those nine teachers' classes showed greater achievement gains than the classes of teachers who did not update grades often enough to participate.

[17] Clustering at the teacher level or two-way clustering by teacher and student yield marginally *smaller* standard errors.

[18] A is coded as 4, B as 3, C as 2, D as 1 and F as 0.

student's class as well. I estimate the effect of additional information on these marks using an ordered Probit model that pools together observations across grading periods and clusters standard errors at the student level. The controls are the same as above with additional grading-period fixed effects. I report marginal effects at the means, but the average of the marginal effects yields similar results.

Effects on full-day attendance and attendance at the classroom level use the same specification and controls as the specifications for GPA and class grades, respectively.

V Results

The Effect of the Treatment on School-to-Parent Contact

Table 2 assesses the effect of the treatment on survey measures of school-to-parent contact. Parents were asked how often the school contacted them during the last month of school regarding their child's grades or schoolwork. During this time all parents had been sent a progress report about their child's grades. The first column shows how much more often the treatment group in high school was contacted by the school than the control group, controlling for baseline GPA and cumulative GPA from students' prior schools.[19] The treatment increased contact from the school regarding their child's grades and schoolwork by 187% relative to the control group. The dependent variable in the second column measures the fraction of people that were contacted by the school more than once. This fraction increases by 158% relative to the control group. The treatment had large effects on both the extensive margin of contact and the intensive margin of contact from the school regarding student grades.

Recall that the experiment was contaminated when the middle school teachers had an employee call their students regarding missing assignments. Mechanically, there should be a positive effect for middle school families since parents did receive messages via the treatment. The employee who contacted families regarding missing work did so for all students—treatment and control—likely resulting in parents being contacted more than once regarding the same missing assignment. While there is no measure of how often parents were contacted with new information, if the contamination were significant, we would expect school-contact effects to be smaller for the middle school sample. The results are considerably weaker for the middle school students. Contact increased by 106% and the fraction contacted increased by 69%.

[19] The results without controls are extremely similar.

A Effects on GPA

Figure 4 tracks average GPA in the treatment and control groups over time. The red vertical line indicates when the treatment began, which is about one month before the first semester ended in mid February. There is a steady decrease in GPA for the control group after the first semester ends in February followed by a spike upward during the final grading period. The treatment group does not experience this decline and still improves in the final grading period. Teachers reported that students work less in the beginning and middle of the semester and "cram" during the last grading period to bring up their GPA, which may negatively affect learning (Donovan, Figlio and Rush, 2006).

The regressions in Table 3 reinforce the conclusions drawn from the graphs described above. Column (1) shows the effect on GPA with no controls. The increase is .15 and is not significant, however the treatment group had a .06 point lower GPA at baseline. Adding a control for baseline GPA raises the effect to .20 points and is significant at the 5% level (column (2)). The standard errors decrease by 35%. The third column adds controls for GPA from students' prior schools and grade level indicators. The treatment effect increases slightly to .23 points. The latter converts to a .19 standard deviation increase in GPA over the control group. The results in Table 4 are estimates of the treatment effect on class grades. Column (1) shows this effect is nearly identical to the effect on final GPA.[20] Column (2) shows the effect on targeted classes—those classes for which a teacher was asked to participate and that teacher provided a grade book so that messages could be sent home regarding missing work. This analysis is underpowered, but the interaction term is positive and not significant (p-value equals .16). Columns (3) and (4) show that math classes had greater gains than English classes (p-values equal .11 and .85, respectively). This effect disparity coincides with the difference in effects shown later for standardized tests scores.

The last column shows the effects for students in which at least one teacher thought additional information would be especially helpful for them. The treatment effect is negative but not significant (p-value equals .24). Most likely there was no differential effect for these students, and if anything the effect appears negative. Teachers appear to have no additional information about whom the treatment would be most helpful for. While teachers generally take in new students every year, the teachers in this sample had known students for three months at the time this variable was measured at baseline.

Even though grading standards are school specific, the impact on GPA is important. In the short run, course grades in required classes determine high school graduation and

[20] The similarity in effects between this unweighted regression on individual grades and the regression on GPA is because there is small variation in the number of classes students take.

higher education eligibility. In the longer run, several studies find that high school GPA is the best predictor of college performance and attainment (for instance Geiser and Santelices, 2007). GPA is also significantly correlated with earnings even after controlling for test scores (Rosenbaum, 1998; French et al., 2010). [21]

B Effects on Final Exams and Projects and Standardized Test scores

Additional information causes exam and final project scores to improve by .16 standard deviations (significant at the 5% level, Table 5). However, teachers enter missing finals as zeros into the grade book. On average, 18% percent of final exams and projects were not submitted by the control group. The effect on the fraction of students turning in their final exam or project is large and significant. Additional information reduces this fraction missing by 42%, or 7.5 percentage points.

Ideally, state-mandated tests are administered to all students, which would help separate out the treatment effect on participation from the effect on their score. Unfortunately, many students did not take these tests, and as shown above, missing a score is correlated with treatment status and treatment-control imbalance—prior test scores of treatment-group students are .26 lower and baseline GPA .13 points lower (results not shown). To see whether those who did not take the test responded to the treatment differently than those who did take the test, I compare the GPA results of those who took the standardized tests with those who did not. Specifically, the indicator for treatment is interacted with an indicator for having a math test score or English test score as follows.

$$GPA_i = \beta_0 + \beta_1 * Treatment_i + \beta_2 * Treatment_i * 1(HasScore_i) + X_i'\gamma + \varepsilon_i$$

Where the variable $HasScore_i$ is an indicator for either having an English test score or having a math test score. The coefficient on the interaction term, β_2, indicates whether those who have a test score experienced different effects on GPA than those who do not have a test score. This achievement effect might correlate with the achievement effect on test scores. If β_2 is large, it suggests how the test-score results might be biased—upwards if β_2 is positive and downwards is β_2 is negative.

Table A.4 shows the results of this analysis. The coefficients on the interaction term for having a score is insignificant (p-value equals .14) but is large and negative. Thus there is some evidence that the treatment effect is smaller for those with test scores compared to

[21] One caveat, however, is that the mechanisms that generate these correlations may differ from the mechanisms underlying the impact of additional information on GPA.

those without, which may bias the estimates on test scores downward.

To account for this potential bias, the effects on math and English test scores are shown with a varying number of controls. The first and fourth columns in Table 6 control only for baseline GPA. The effect on math and English scores are .08 and -.04 standard deviations respectively. Columns (2) and (5) add controls for prior test scores, demographic characteristics and test subject. The treatment effect on math scores is .21 standard deviations, but remains near zero for English scores. Finally, if the treatment induces lower performing students to take the test, then those with higher baseline GPA might be less affected by this selection. This means we might see a positive coefficient on the interaction term between baseline GPA and the treatment. Columns (3) and (6) add this interaction term. While the interaction term is small for English scores, for math scores it implies that someone with the average GPA of 2.01 has a .20 standard deviations higher math score due to the additional information provided to their parents.[22]

This disparity between math and English gains is not uncommon. Bettinger (2010) finds financial incentives increase math scores but not English scores and discusses several previous studies (Reardon, Cheadle, and Robinson, 2008; Rouse, 1998) on educational interventions that exhibit this difference as well. There are three apparent reasons the information intervention may have had a stronger effect on math than English. First, the math teachers in this sample provided more frequent information on assignments that allowed more messages to be sent to parents. Potentially, this frequency might mean students fall less behind.[23] Second, 30% of students are classified as "limited-English proficient," which means they are English-language learners and need to pass a proficiency test three years in a row to be reclassified. Looking at class grades, these students tend to actually perform *better* in English classes, though interacting the treatment with indicators for language proficiency and English classes yields a large and negative coefficient (results not shown). In contrast, this coefficient is negative but 75% smaller when the interaction term includes an indicator for math classes rather than English classes. This means that the treatment effect for students with limited English skills is associated with smaller gains for English than math, which may in part drive the disparity in effects. Lastly, math assignments might provide better preparation for the standardized tests compared to English assignments if they more closely approximate the problems on the test.

[22] This marginal effect at the mean is significant at the 5% level.

[23] This theory is difficult to test since there is no within-class variation in grade-book upkeep or message frequency conditional on missing an assignment.

C Effects on Behaviors and Assignment Completion

The effects on work habits and cooperation are consistent with the effects on GPA. Figure 5 shows that the treatment group exhibits less unsatisfactory work habits than control group, on average. Figure 6 shows that excellent work habits increase steadily for the treatment group over time. Excellent cooperation, shown in Figure 8, dips in the middle of the semester but rises at the end. The average levels of uncooperative behavior exhibit a similar pattern to unsatisfactory work habits (Figures 7).

Table 7 provides the ordered-Probit estimates for work habits and cooperation (Panel A). Additional information reduces the probability of unsatisfactory work habits by 24%, or a six-percentage point reduction from the overall probability at the mean. This result mirrors the effect on excellent work habits for high school students, which increases by seven-percentage points at the mean. The probability of unsatisfactory cooperation is reduced by 25% and the probability of excellent cooperation improves by 13%.

Panel B shows OLS estimates of the effects on attendance. The effect on full-day attendance is positive though not significant, however full-day attendance rates are already above 90% and students are more likely to skip a class than a full day. Analysis at the class level shows positive and significant effects. The treatment reduces classes missed by 28%. The final column of Panel B contains the estimated probability of missing an assignment. The average student does not turn in 20% of assignments. Assignments include all work, classwork and homework, and the grade books do not provide enough detail to discern one from the other.[24] At the mean, the treatment decreases the probability of missing an assignment by 25%.

The behavior effects indicate that one mechanism the additional information operates through is increased productivity during school hours. Assignments may be started in class but might have to be completed at home if they are not finished during class (e.g. a lab report for biology or chemistry, or worksheets and writing assignments in history and English classes). If students do not complete this work in class due to poor attendance or a slow work pace, they may not do it at home. The information treatment discourages poor attendance and low in-class productivity, which in turn may increase assignment completion.

D Mechanisms

The goal of this is section is to understand how parents used the additional information provided by the treatment, how students responded outside of school, and how the information affected parents.

[24] Several teachers said that classwork is much more likely to be completed than work assigned to be done at home.

How Parents Used the Additional Information

Panel A of Table 8 shows how parents used the information. Parents were asked how many privileges they took away from their child in the last month of school, which increased by nearly 100% for the treatment group (column (1)). The most common privilege revoked by parents involved electronic devices—cell phones, television, Internet use and video games—followed by seeing friends.[25] Parents also spoke about college more often to their child, perhaps emphasizing the future returns to schooling in addition to the threat of punishment. Interestingly, parents in the treatment group asked about homework less during the last month of school, though the coefficient is not significant. The negative sign could be due to parents' interpretation of the question in that they exclude messages from the school from their count. Or, parents might substitute away from asking about this from their children if they realize the information provided via the treatment is more reliable. Lastly, children were asked how often they received help with their homework from their parents on a three point scale ("never," "sometimes," or "always," coded from zero to two). The final column of Panel A shows the coefficient is positive but not significant. Overall, more information appears to facilitate parents ability to incentivize their children to do well in school.

How Students Responded

The first three columns of Panel B show how students' work habits changed outside of school. Tutoring attendance over the semester increased 42%. The coefficient is marginally insignificant at standard levels (p-value equals .11). Tutoring was offered by teachers after school for free. The positive effect on tutoring is at least partially due to several teachers' requirement that missing work be made up during their after school tutoring to prevent cheating. The second column shows the effect on whether students did their homework at the last minute, which was coded from zero to two for "never," "sometimes" or "always." Students in the treatment group were significantly less likely to do their homework at the last minute. Nonetheless, student study hours at home did not significantly increase, which implies that most of the gains in achievement are due to improved work habits at school. The remaining two columns of Panel B show students' valuations of schooling on a four-point scale. Students in the treatment group are more likely to say grades are important, but no more likely to say that college is important. One interpretation of these results is that grades are important because students will be punished if they do not do well, but their intrinsic valuation of schooling has not changed.

[25] An open-ended question also asked students how their parents respond when they receive good grades. 41% said their parents take them out or buy them something, 50% said their parents are happy, proud or congratulate them, and 9% said their parents do not do anything.

Information Problems and Information Demand

Panel C shows that some parents lacked awareness of the information problems with their child regarding school work. Column (1) reports the answers to the question, "Does your child not tell you enough about his or her school work or grades?" Parents in the treatment group are almost twice as likely to say yes as parents in the control group. This answer may reflect parents' about their understanding of the A–F grading system. 11% of parents responded that they did not understand it or were unsure of the meaning of the scale. 40% of parents did not graduate high school and many are not from the United States. Other countries use different grading scales, which might contribute to parents' unfamiliarity and their reliance on their children for information.[26]

Coinciding with the awareness of information problems, the second and third columns show that parents increased their demand for information regarding their child's schoolwork and progress. Over the last semester, parents in the treatment group were much more likely to contact the school regarding the latter (85% more), and this is corroborated by the school's data on parent-teacher conference attendance, which increased by 53%. The guidance counselor reported that parents arranged meetings with her because of the additional information. This increased contact could partly be due to the limited nature of the additional information in the messages home and the conflict it created in the household. The information came directly from the grade book and no further details could be provided. If a child denied missing an assignment, provided an excuse or parents otherwise needed further information, parents might have wanted to speak directly to the counselor or teacher. The treatment appears to make parents aware of communication problems between themselves and their children, which in turns spurs demand for information from the school.

Finally, the last column reports answers to whether parents agree they can help their child do their best at school. Parents in the treatment group are 16 percentage points more likely to say yes.

Ruling out Alternative Explanations

The fact that the randomization was at the student level, within classrooms, raises two potential concerns. The first concern is teachers could have artificially raised treatment-group student grades to reduce any hassle from parental contact. If this were the case, the grade improvements observed in the treatment group would not be due to the effect of additional information on student effort and would not correspond to any actual improvement

[26] This knowledge deficit is salient enough to LAUSD that some schools have offer free classes to parents to teach them about the school system, graduation requirements, what to ask during conferences and other school-related information.

in student performance. A second concern is that teachers paid more attention to treatment-group students at the expense of attention for control-group students. This reallocation of attention to treatment-group students could reduce achievement for control students and bias effects away from zero. While these are potential issues, several results undermine support for these interpretations.

The most definitive results contradicting these interpretations are the significant effects on measures of student effort and parental investments that are less likely to be manipulated by teachers. The treatment group has higher attendance rates, higher levels of student-reported effort such as tutoring attendance and timely work completion, and a greater fraction of completed assignments. These results suggest that students indeed exerted more effort as a result of the information treatment. Consistent with this interpretation, the survey evidence from parents suggests that treatment-group parents took steps to motivate their children in response to the additional information beyond those of control-group parents, such as more intensive use of incentives.

It is also plausible that teachers who did not participate in the information intervention were less aware of who is in the treatment group versus the control group and therefore less likely to change their behavior as a result of the experiment. Consistent with the results above, the class-level analysis shows that students' grades also improved in the classes of these non-participating teachers (Table 4, column two).

Third, an analysis of treatment effects on control group students provides some evidence on whether the control group's grades increased or decreased as a result of the treatment. Though the experiment was not designed to examine peer effects, random assignment at the student level generates classroom-level variation in the fraction of students treated. Table A.5 shows the results from a regression of control students' class grades on the fraction of students treated in each respective class. While not statistically significant (p-value equals .27), the point estimate implies a positive impact of the fraction of students treated in a given classroom on the control students (a 25 percentage point increase in the fraction of students treated in a given classroom causes control group students' grades to increase by .14 points). This suggests that the gains observed among treatment students did not come at the expense of control students. To the contrary, there may have been positive spillovers onto control-group students' achievement that bias the effects of additional information toward zero.

VI Middle School Results

Table 9 summarizes the effects on achievement and effort-related outcomes for middle school students, which are mostly small and not significantly different from zero. These results are consistent with the effects on how parents used the additional information, how children responded, and parents' awareness and demand for information (Table 10). Based on these results and the contamination, it is difficult to discern what effect the treatment would have had on younger students.

There are several reasons the additional information may have had less effect on younger children. First, the middle school students have less margin to improve: Their GPA is almost a full standard deviation higher than high school students' GPA, middle school students miss 7.5% of their assignments compared to high school students who miss 20% of their assignments, and attendance and behavior are also better for middle school students. However if this were the only cause for small effects, there could still be an impact on students who were lower-performing at baseline. Unfortunately the study is underpowered to examine subgroups in the middle school, but point estimates show students with higher GPA respond more positively to additional information (results not shown). A second reason there might be smaller effects for middle school students is that parents might be able to control younger children better than older children. It might be less costly for parents to motivate their children or information problems arise less frequently. There is some support for this hypothesis since teacher-measured behavior at baseline is better for middle school students than high school students, which might correlate with parents' ability to control their child. Third, the repeated messages to middle school parents through the information treatment and the contamination by the school employee may have annoyed them. If they had already resolved an issue such as a missing assignment, receiving a second message regarding that work might have been confusing and frustrating. Parents could have viewed the information treatment as less reliable given the lack of coordination about school-to-parent contact and started ignoring it, which might explain the small negative coefficients on several middle school outcomes. Lastly, parents of middle-school students might already obtain information about their child's education more actively, which is reflected in the higher parent-teacher conference attendance. In addition, a comparison of the control groups in the high school and middle school shows that parents of middle school students are more likely to take away privileges from their children, be aware of information problems, contact the school about their child's grades, and feel that they can help their child try their best than parents of high school students in the control group.[27] It is possible that the contamination caused

[27]Results available upon request.

this higher level of involvement—meaning messages home did affect middle school parents—or it could be that these parents were already more involved than high school parents. If the latter, it leaves open the question of why this involvement wanes as children get older; perhaps parents perceive they have less control of their child's effort or that they no longer know how to help them. In short, the effect of additional information on younger children is inconclusive.

VII Conclusion and Cost effectiveness

This paper uses an experiment to answer how information asymmetries between parents and their children affect human capital investment and achievement. The results show these problems can be significant and their effect on achievement large. Additional information to parents about their child's missing assignments and grades helps parents motivate their children more effectively, but also changes parents' beliefs about the quality of information they receive from their child. Parents become more aware that their child does not tell them enough about their academic progress. These mechanisms drive an almost .20 standard deviation improvement in math standardized test scores and GPA for high school students. There is no estimated effect on middle-school family outcomes, however there was severe contamination in the middle school sample. One positive aspect of this contamination is that it reflects teachers' perceptions of the intervention. In response to this experiment, the school and a grade-book company collaborated to develop a feature that automatically text messages parents about their child's missing assignments directly from teachers' grade books.

Importantly, this paper demonstrates a potentially cost-effective way to bolster student achievement: Provide parents frequent and detailed grade-book information. Contacting parents via text message, phone call or email took approximately three minutes per student. Gathering and maintaining contact numbers adds five minutes of time per child, on average. The time to generate a missing-work report can be almost instantaneous or take several minutes depending on the grade book used and the coordination across teachers.[28] For this experiment it was roughly five minutes. Teacher overtime pay varies across districts and teacher characteristics, but a reasonable estimate prices their time at $40 per hour. If teachers were paid to coordinate and provide information, the total cost per child per .10 standard-deviation increase in GPA or math scores would be $156. Automating aspects of this process through a grade book could reduce this costs further. Relative to other effective

[28]Some grade book programs can produce a missing assignment report for all of a student's classes.

interventions targeting adolescent achievement, this cost is quite low.

However it is important to consider how well these results extrapolate to other contexts. While the student population is fairly representative of a large, urban school district like Los Angeles Unified, there are several parameters of the education-production function that determine the effectiveness of increasing information to parents. The framework in Section II illustrates this point. Two salient factors are teacher and parent characteristics. Teacher quality affects both the capability of the school to provide information and the impact of student effort on achievement. If teachers do not frequently grade assignments, it is difficult to increase the amount of information to parents. Nine of the fourteen teachers in the sample maintained their grade books often enough to effectively participate in the experiment. It is not known whether this is a typical amount or not. In this experiment, the positive effects spilled over to classes for which there was little grade book information. Also, teachers at this school generally accepted work after the requested due date. Parents were notified about missing assignments that they could still help their child complete. This scheme might allow parents to overcome a child's high discount rate by immediately monitoring and incentivizing the work they must make up. The results may be weaker if parents are only notified about work prior to the due date or about work students can no longer turn in. Even if information can be provided, and this engenders greater effort from students, the effects on achievement depend on the quality of the work teachers supply. Students may work harder but show no gains in measures of learning. For parents, the effects may differ by demographic characteristics as well. Information changes parental beliefs, and this effect may apply less to parents who know the school system well and have greater resources to invest in their children. Finally, the treatment lasted six months. The negative information about academic performance could create tension at home that might impact outcomes differently over the long run. [29]

Overall, the results support a model of human capital investment that incorporates information asymmetries between parents and their children. This experiment suggests one mechanism in which providing information lowers monitoring costs for parents and facilitated incentives; additional information improved student effort and achievement. More broadly, parental monitoring is positively linked to number of behavioral outcomes, such as crime and health behaviors (Kerr and Stattin, 2000). Future research could examine how parent-child information frictions affect other investments and outcomes as well.

[29] The cost-effectiveness analysis excludes this potential cost to parents and children.

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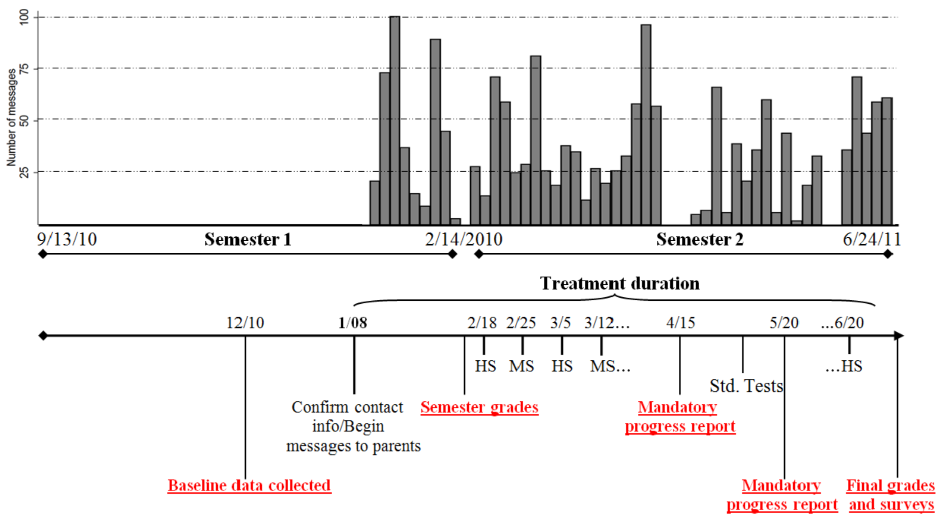

Figure 1: Timeline

This figure shows the timeline of the experiment. Above the timeline is a chart of the frequency of messages sent to parents. Each bar signifies the number of messages sent over a three-day period and corresponds to the timeline dates below. The abbreviations HS and MS indicate that messages were sent to families of high school (HS) students families on alternate weeks with respect to middle school (MS) students families. "Std. tests" shows when the state-mandated standardized tests took place.

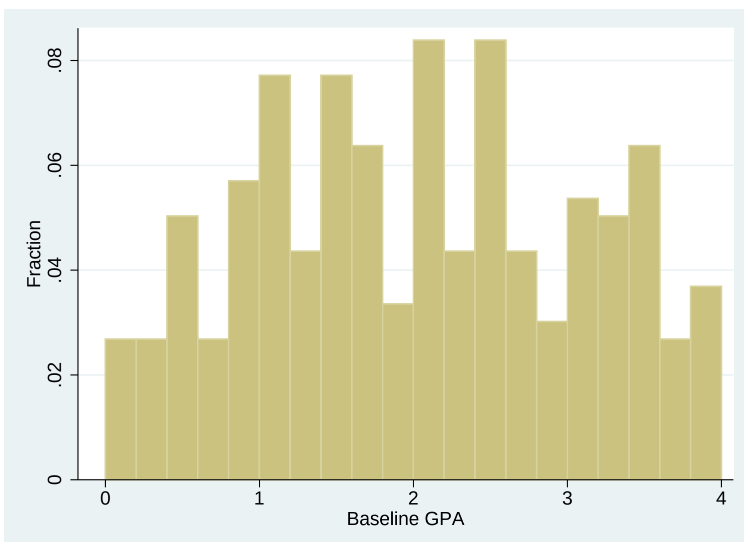

Figure 2: Distribution of baseline GPA

This figure shows the distribution of baseline GPA for all grades. Baseline GPA is calculated from a student's mid-semester progress report, which was two months prior to the start of the treatment.

Figure 3: Distribution of behaviors at baseline

This figure shows the distribution of baseline work habits and cooperation for high school students. Work habits and cooperation are measured as excellent, satisfactory and unsatisfactory. Students receive these marks for each class they take. Several teachers stated that work habits reflect how on task students are during class, while cooperation measures their interactions with the teacher and peers. These measures were drawn from students' mid-semester progress report, which was two months prior to the start of the treatment.

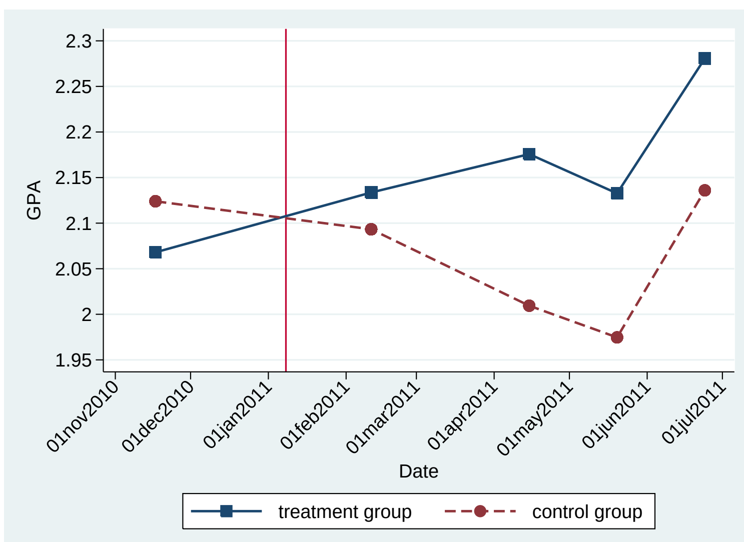

Figure 4: GPA over time for high school students

This graph plots the GPA of high school students in the treatment and control group over time. Each point represents the average GPA in a group calculated from progress report grades. The vertical red line indicates when the treatment began. To hold the composition of the sample constant over time, this plot excludes students who left the school prior to the end of the second semester.

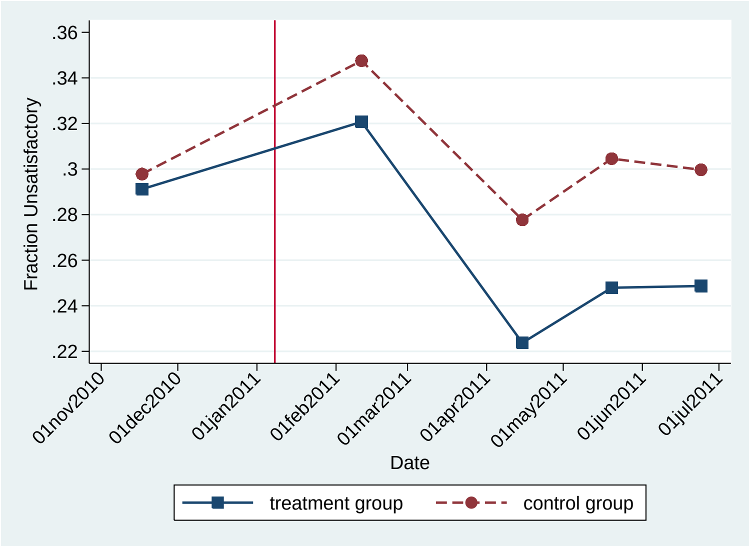

Figure 5: Fraction of work habits marked unsatisfactory over time

This graph plots the fraction of unsatisfactory work habit marks for the high school treatment and control groups over time. Work habits are graded as either excellent, satisfactory or unsatisfactory. Each point is calculated using progress report marks from each class. The vertical red line indicates when the treatment began. To hold the composition of the sample constant over time, this plot excludes students who left the school prior to the end of the second semester.

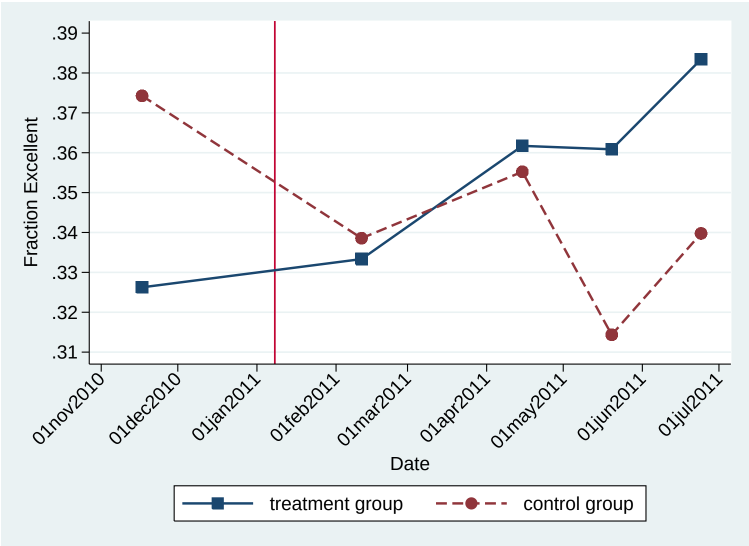

Figure 6: Fraction of work habits marked excellent over time

This graph plots the fraction of excellent work habit marks for the high school treatment and control groups over time. Work habits are graded as either excellent, satisfactory or unsatisfactory. Each point is calculated using progress report marks from each class. The vertical red line indicates when the treatment began. To hold the composition of the sample constant over time, this plot excludes students who left the school prior to the end of the second semester.

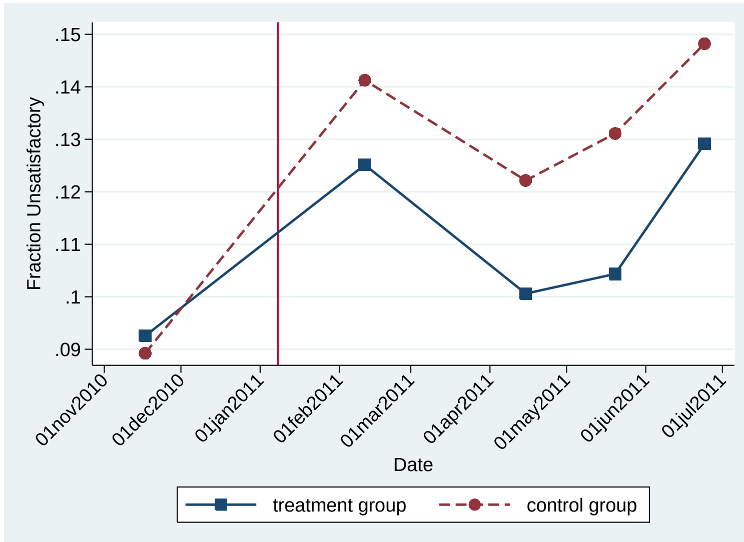

Figure 7: Fraction of cooperation marks rated unsatisfactory over time

This graph plots the fraction of unsatisfactory cooperation marks for the high school treatment and control groups. Cooperation is graded as either excellent, satisfactory or unsatisfactory. Each point is calculated using progress report marks from each class. The vertical red line indicates when the treatment began. To hold the composition of the sample constant over time, this plot excludes students who left the school prior to the end of the second semester.

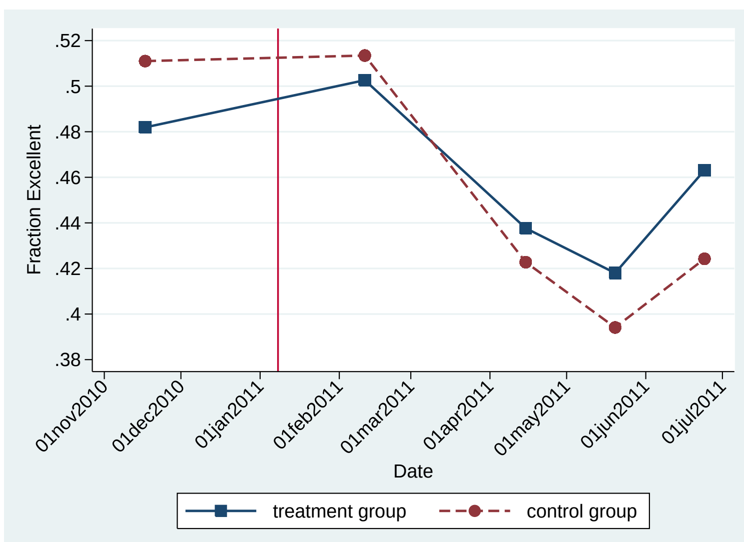

Figure 8: Fraction of cooperation marks rated excellent over time

This graph plots the fraction of unsatisfactory cooperation marks for the high school treatment and control groups over time. Cooperation is graded as either excellent, unsatisfactory or excellent. Each point is calculated from progress report marks from each class. The vertical red line indicates when the treatment began. To hold the composition of the sample constant over time, this plot excludes students who left the school prior to the end of the second semester.

Table 1: Summary Statistics and Treatment-Control Group Balance

Panel A.	**Sample balance including attriters**					
	Control Mean	Treatment Mean	Difference	p-value	Students	Obs.
Female	0.363	0.463	0.099	0.078	306	306
Attendance	0.928	0.942	0.014	0.278	306	306
Baseline GPA	2.019	1.995	-0.024	0.848	298	298
Prior GPA	2.173	2.043	-0.130	0.282	252	252
Asian	0.24	0.219	-0.021	0.664	306	306
Black	0.021	0.031	0.011	0.559	306	206
Hispanic	0.699	0.725	0.026	0.612	306	306
Parent graduated HS	0.205	0.231	0.026	0.588	306	306
Free/Reduced Lunch	0.89	0.869	-0.022	0.563	306	306
Work habits unsatisfactory	0.326	0.308	-0.019	0.585	297	1953
Cooperation unsatisfactory	0.111	0.105	0.006	0.751	297	1952
Work habits excellent	0.354	0.310	-0.044	0.207	297	1953
Cooperation excellent	0.487	0.458	-0.029	0.385	297	1952

Panel B.	**Sample balance excluding attriters**					
	Control Mean	Treatment Mean	Difference	p-value	Students	Obs.
Female	0.382	0.462	0.079	0.182	279	279
Attendance	0.949	0.952	0.003	0.797	279	279
Baseline GPA	2.124	2.068	-0.056	0.658	272	279
Prior GPA	2.267	2.137	-0.130	0.289	228	228
Asian	0.243	0.238	-0.005	0.924	279	279
Black	0.022	0.028	0.006	0.753	279	279
Hispanic	0.691	0.706	0.015	0.784	279	279
Parent graduated HS	0.213	0.238	0.025	0.626	279	279
Free/Reduced lunch	0.904	0.888	-0.016	0.657	279	279
Work habits unsatisfactory	0.298	0.291	-0.007	0.846	279	1804
Work habits excellent	0.374	0.326	-0.048	0.188	279	1804
Cooperation unsatisfactory	0.089	0.093	0.003	0.855	279	1803
Cooperation excellent	0.511	0.482	-0.029	0.388	279	1803

Note: p-values are for tests of equality of means across the treatment and control group. Differences across work habits and cooperation are estimated by a regression of the behavior on treatment status with standard errors clustered by student. Baseline data are missing for students who enrolled in the school after the school year began. The "Students" column reports the number of student-level observations used in the analysis. The "Obs." column shows the total number of observations. The number of observations differs from the number of students for work habits and cooperation because a student receives these marks for each class he or she takes.

Table 2: Contact from the School Regarding Grades

Dependent variable	(1) School contact to parent	(2) Contacted more than once	(3) School contact to parent	(4) Contacted more than once
Treatment	2.125***	0.453***	1.445***	0.308***
	(0.370)	(0.068)	(0.350)	(0.111)
Baseline GPA	0.100	-0.105**	-0.191	-0.074
	(0.411)	(0.052)	(0.320)	(0.120)
Prior GPA	-0.125	0.100*	-0.408	-0.147
	(0.341)	(0.051)	(0.420)	(0.123)
Control mean	1.134	0.286	1.360	0.448
Sample	H.S.	H.S.	M.S.	M.S.
Observations	183	183	80	80
R-squared	0.173	0.248	0.324	0.246

The dependent variable is drawn from surveys of parents. Parents were asked how many times they were contacted by the school regarding their child's grades or schoolwork during the last month of school. Columns (1) and (3) use the number of times contacted by the school as the dependent variable while columns (2) and (4) use an indicator for whether a parent was contacted more than one time. The first two columns are for the high school sample (HS), while the remaining two columns are for the middle school sample (MS), where the experiment was contaminated. Baseline GPA is calculated from students' mid-semester progress reports from two months before the experiment began. Prior GPA is students' cumulative GPA from middle school and beyond. Strata and grade-level indicators are also included in each regression. Robust standard errors are in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 3: GPA effect on High School Students

	(1)	(2)	(3)
Dependent variable	GPA	GPA	GPA
Treatment	0.145	0.203**	0.229**
	(0.143)	(0.093)	(0.090)
Baseline GPA		0.931***	0.760***
		(0.060)	(0.071)
Prior GPA			0.334***
			(0.072)
Grade 10			-0.248**
			(0.119)
Grade 11			-0.164
			(0.117)
Observations	279	279	279
R-squared	0.004	0.601	0.645

The dependent variable is students' end-of-semester GPA. Data used in these regressions are from administrative records. Baseline GPA is calculated from students' mid-semester progress reports from two months before the treatment began. Prior GPA is students' cumulative GPA from middle school and beyond. Strata indicators are also included in each regression. High school in this sample includes only grades nine through eleven because the school had just opened. Robust standard errors are in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Effects on Grades

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Class Grade	Class Grade	Class Grade	Class Grade	Class Grade
Treatment	0.231***	0.188**	0.208**	0.232**	0.351***
	(0.088)	(0.095)	(0.089)	(0.090)	(0.135)
Treatment*Target		0.120			
		(0.086)			
Treatment*Math class			0.212		
			(0.132)		
Treatment*English class				0.022	
				(0.119)	
Treatment*Help					-0.204
					(0.175)
Students	279	279	279	279	279
Observations	2,224	2,224	2,224	2,224	2,224
R-squared	0.399	0.438	0.417	0.405	0.400

The dependent variable in these regressions is each students' class grade, which is coded into a four-point scale from their letter grades. Data used in these regressions are from administrative records. Each student typically takes eight classes. Grades marked incomplete are coded as missing. Additional controls in each regression are students' baseline GPA, prior GPA, grade-level indicators and strata indicators. Baseline GPA is calculated from students' mid-semester progress reports from two months before the treatment began. Prior GPA is students' cumulative GPA from middle school and beyond. Standard errors clustered by student are in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Effects on Final Exams and Projects

	(1)	(2)	(3)	(4)
Dependent variable:	All Scores	Math Scores	English Scores	No Score
Treatment	0.160**	0.180*	0.329**	-0.075***
	(0.081)	(0.110)	(0.106)	(0.034)
Students	279	239	100	279
Observations	639	239	100	676
R-squared	0.347	0.430	0.465	0.184

All exam and final project scores are standardized by class to have a mean equal to zero and a standard deviation equal to one. Data in these regressions are from teacher grade books. Additional controls not shown are baseline GPA, prior GPA, grade-level indicators and strata indicators. Baseline GPA is calculated from students' mid-semester progress reports from two months before the experiment began. Prior GPA is students' cumulative GPA from middle school and beyond. The final column shows the effect of the treatment on not having score, excluding excused absences. If a student does not have a score it means they did not turn in any test or project. 18% of tests or final projects were not turned in by the control group. Standard errors clustered by student are in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Effects on Standardized Test Scores

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Math Score	Math Score	Math Score	English Score	English Score	English Score
Treatment	0.077	0.212**	-0.184	-0.039	0.008	0.036
	(0.107)	(0.102)	(0.236)	(0.226)	(0.091)	(0.209)
Baseline GPA	0.311***	0.245**	0.119	0.539***	0.339***	0.346***
	(0.076)	(0.091)	(0.104)	(0.083)	(0.078)	(0.101)
Prior GPA	0.292***	0.259***	0.198***	0.140*	0.075	0.018
	(0.084)	(0.077)	(0.081)	(0.078)	(0.070)	(0.071)
Treatment*baseline GPA			0.192**			-0.013
			(0.101)			(0.090)
Additional controls	No	Yes	Yes	No	Yes	Yes
Observations	256	256	256	257	257	257
R-squared	0.306	0.457	0.468	0.337	0.605	0.605

This table reports the effect of the treatment on the state-mandated test, the California Standards Test, for high school students. Scores are standardized by test subject to have a mean of zero and a standard deviation equal to one. The additional controls not shown above are prior test scores, race, sex, test subject, language spoken at home and free or reduced-price lunch status. Baseline GPA is GPA calculated from students' mid-semester progress reports two months before the treatment began. Prior GPA is students' cumulative GPA from middle school and beyond. Robust standard errors are in parentheses.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: Effects on Behaviors

	In-Class Work Habits		**In-Class Cooperation**	
Dependent variable	Pr(Unsatisfactory)	Pr(Excellent)	Pr(Unsatisfactory)	Pr(Excellent)
Treatment	-0.061***	0.069***	-0.024**	0.056**
	(0.021)	(0.022)	(0.011)	(0.024)
Predicted probability	0.256	0.339	0.096	0.432
Students	279	279	279	279
Observations	8,795	8,795	8,795	8,795

		Attendance		**Assignment Completion**
Dependent Variable:	Full-day Rate	By-Class Rate	Classes Missed	Pr(Missed Asst.)
Treatment	1.675	2.879*	-1.401**	-0.049***
	(1.146)	(1.540)	(0.633)	(0.018)
Control mean	92.81	88.505	5.350	0.197
Students	278	278	278	279
Observations	278	2,252	2,252	27,297

The upper panel reports the effects of the treatment on the probability of unsatisfactory and excellent work habits or cooperation. These behaviors are measured as excellent, satisfactory and unsatisfactory. The coefficients reported are marginal effects at the means from ordered Probit models. Controls not shown are baseline GPA, cumulative GPA from prior schools, grading-period indicators, grade-level indicators and strata indicators. Baseline GPA is GPA calculated from students' mid-semester progress reports two months before the treatment began. Prior GPA is students' cumulative GPA from middle school and beyond. The number of observations differs from the number of students because each student receives a behavior mark for each class and for each of the four grading periods. In the lower panel, full-day attendance measures whether a student attended the majority of the school day, by-class measures attendance for each class, and classes missed measures how many classes a student did not attend over the semester, by course. Lastly, the probability of missing an assignment is reported as the marginal effect at the means from a Probit model. Standard errors clustered at the student level are in parentheses.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Families' Responses to Additional Information

Panel A.	How Parents Used the Information				
Dependent variable	Privileges	Talk College	Ask HW	Help Kid	
Treatment	1.660**	2.611*	-2.533	0.088	
	(0.718)	(1.415)	(1.688)	(0.069)	
Control Mean	1.729	7.637	18.773	0.210	
Data source	Parent	Parent	Parent	Child	
Observations	180	183	184	183	
R-squared	0.168	0.163	0.048	0.091	
Panel B.	**How Students Responded**				
Dependent variable	Tutoring	Homework last minute	Study hours	Grades important	College important
Treatment	5.978	-0.227*	0.146	0.234**	0.040
	(3.763)	(0.116)	(0.263)	(0.102)	(0.074)
Control Mean	14.250	1.202	0.380	3.681	3.639
Data source	Child	Child	Child	Child	Child
Observations	154	152	153	155	154
R-squared	0.086	0.087	0.160	0.181	0.133
Panel C.	**Information Problems and Information Demand**				
Dependent variable	Information problem?	Contacted School	Attended Conference	Can help	
Treatment	0.195***	1.783***	0.079*	0.161**	
	(0.070)	(0.668)	(0.046)	(0.072)	
Control Mean	0.210	2.102	0.150	0.600	
Data source	Parent	Parent	School	Parent	
Observations	176	179	181	181	
R-squared	0.160	0.147	0.105	0.101	

All columns show the effects of the information treatment on parents. Treatment effects are estimated using regressions that control for baseline GPA, prior GPA, strata indicators and grade-level indicators. Baseline GPA is GPA calculated from students' mid-semester progress reports two months before the experiment began. Prior GPA is students' cumulative GPA from middle school and beyond. Data source indicates whether the dependent variable came from a parent's survey response, a child's survey response, or school records. Robust standard errors are in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 9: Middle School Student Outcomes

Dependent Variable	Treatment	Standard Error	Students	Observations
GPA	-0.108	(0.102)	149	149
Final Exams	-0.054	(0.199)	87	87
Math CST	0.034	(0.119)	139	139
English CST	-0.017	(0.13)	145	145
Pr(missed assignment)	0.005	(0.01)	87	7,692
Work habits unsatisfactory	0.019	(0.019)	149	2,635
Work habits excellent	-0.041	(0.039)	149	2,635
Cooperation unsatisfactory	0.004	(0.009)	149	2,635
Cooperation excellent	-0.021	(0.038)	149	2,635
Full-day attendance	-1.101	(0.684)	149	148
By-class attendance	-1.918	(1.24)	149	1,933
Classes missed	0.782	(0.49)	149	1,933

This table summarizes the results of the treatment effects on middle-school student outcomes, where the experiment was contaminated. The results shown are the coefficients on the treatment indicator in a regression that controls for baseline GPA, prior GPA, grade-level indicators and strata indicators. The treatment effect on missing an assignment is the marginal effect at the means from a Probit model. Work habits and cooperation treatment effects are the marginal effects at the means from an ordered Probit model. All remaining results are estimated by OLS. Where the number of observations differs from the number of students, this is because each student receives a behavior mark for each class as well as each of the four grading periods. By-class attendance is an end-of-semester measure given for each class a student takes. The data for these regressions are drawn from administrative records. Final exam scores could not be obtained for the sixth grade. Standard errors clustered by student are in parentheses.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 10: Middle School Family Survey Outcomes

Dependent Variable	Treatment	Standard Error	N
How Parents Used the Information			
Privileges taken last month	0.260	(0.320)	79
Talk about college	-0.548	(1.325)	82
Ask about homework	-4.532	(2.745)	81
Help with homework	-0.186	(0.111)*	65
How Students responded			
Tutoring	0.845	(1.500)	65
HW last minute	-0.001	(0.120)	64
Study hours	-0.267	(0.322)	60
Grades important	-0.167	(0.190)	65
College important	-0.152	(0.135)	65
Information Problems and Information Demand			
Information problem?	0.100	(0.089)	80
Contacted School	-0.460	(0.601)	81
Can help	0.060	(0.077)	82

The dependent variables in these OLS regressions are from parent and student surveys. Additional controls in these regressions are baseline GPA, grade-level indicators and strata indicators. These results are for families of middle school students only, where the experiment was contaminated. Robust standard errors are in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Appendix for Online Publication

Table A.1: Attrition

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Left the Sample			
Treatment	-0.016	-0.012	0.008	0.026	0.020	0.025
	(0.029)	(0.026)	(0.018)	(0.031)	(0.031)	(0.027)
7th grade		0.005	-0.032			
		(0.025)	(0.026)			
8th grade		0.061	-0.017			
		(0.046)	(0.027)			
Baseline GPA			-0.058			-0.001
			(0.037)			(0.022)
Prior GPA			0.007			-0.047*
			(0.036)			(0.027)
Full-day attendance			0.496			-0.838***
			(0.306)			(0.255)
Female			-0.012			-0.003
			(0.022)			(0.029)
Black			0.937***			0.160
			(0.115)			(0.121)
Hispanic			-0.160			0.067
			(0.133)			(0.044)
Asian			-0.107			0.099**
			(0.132)			(0.045)
Free/Reduced Lunch			0.027			-0.026
			(0.018)			(0.040)
10th grade					0.089**	0.042
					(0.041)	(0.034)
11th grade					0.039	0.036
					(0.036)	(0.038)
Control mean	0.041			0.068		
Sample	MS	MS	MS	H.S.	H.S.	H.S.
Observations	156	156	156	306	306	306
R-squared	0.031	0.050	0.500	0.037	0.050	0.243

The dependent variable in these regressions is an indicator for having left the school. Columns (1)-(3) show the correlates of leaving for the middle school (MS). Baseline GPA is from mid-semester report cards two months before the treatment began and prior GPA is students' cumulative GPA from previous grades. Columns (4)-(6) show these correlates for the high school (HS) sample only. Robust standard errors are in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table A.2: Survey Response Correlates

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Responded to Survey			
Treatment	0.043	0.033	0.036	0.026	0.013	0.015
	(0.056)	(0.055)	(0.050)	(0.057)	(0.056)	(0.053)
Baseline GPA		-0.067**	0.042		-0.062**	0.031
		(0.029)	(0.030)		(0.030)	(0.032)
9th grade		0.219***	0.224***		0.122*	0.129*
		(0.069)	(0.062)		(0.071)	(0.066)
10th grade		0.100	0.089		0.056	0.046
		(0.074)	(0.067)		(0.076)	(0.070)
Full-day attendance		0.765***	0.651***		0.914***	0.809***
		(0.265)	(0.241)		(0.274)	(0.255)
Female			-0.045			0.000
			(0.052)			(0.055)
Hispanic			0.305***			0.300***
			(0.108)			(0.114)
Asian			-0.225*			-0.175
			(0.115)			(0.121)
Free/Reduced lunch			0.075			0.108*
			(0.059)			(0.062)
Control Mean	0.582			0.493		
Sample	Parents	Parents	Parents	Children	Children	Children
Observations	306	306	306	306	306	306
R-squared	0.002	0.073	0.252	0.001	0.053	0.200

The dependent variable in these OLS regressions is an indicator for responding to the survey. Columns (1)-(3) show the correlates of response for the parent survey. Columns (4)-(6) show these correlates for the child survey. The control mean shows the percentage of control-group members who responded to the survey. These results are for families of high school students only. Robust standard errors are in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table A.3: Missing CST Scores

Dependent variable	(1) Missing math	(2) Missing math	(3) Missing math	(4) Missing English	(5) Missing English	(6) Missing English
Treatment	-0.054	-0.060*	-0.065*	-0.047	-0.051	-0.056
	(0.033)	(0.033)	(0.035)	(0.032)	(0.032)	(0.035)
Baseline GPA		-0.050*	-0.041		-0.053*	-0.050
		(0.028)	(0.028)		(0.021)	(0.031)
Control mean	0.110			0.103		
Additional controls	No	No	Yes	No	No	Yes
Observations	279	279	279	279	279	279
R-squared	0 .010	0.010	0.122	0.008	0.090	0.173

The dependent variable in these OLS regressions is an indicator for having no test score. Additional controls include prior GPA, prior scores, test-subject indicators and demographic characteristics. Robust standard errors are in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table A.4: Sample selection and test scores

Dependent variable	(1) GPA
Treatment	0.700**
	(0.356)
Treatment*(has score)	-0.546
	(0.369)
Observations	279
R-squared	0.653

This table shows the treatment effect on GPA, and interacts the treatment variable with an indicator for whether or not a student has a math standardized test score an English standardized test score. These effects are estimated with an OLS regression that controls for baseline GPA, GPA from a students prior school, grade-level indicators and strata indicators. Results are shown for high school students only. All data are from administrative records. Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table A.5: Peer Effects

	(1)
Dependent variable	Class Grade
Fraction treated	0.578
	(0.500)
Observations	1042
R-squared	0.417

This table shows how the fraction of the class treated affects class grades for the control group. This effect is calculated using an OLS regression that restricts the sample to the control group and controls for baseline GPA, GPA from a students prior school, grade-level indicators and strata indicators. Results are shown for high school students only. All data are from administrative records. Standard errors are clustered at the teacher level accounting for the 19 clusters using a Wild bootstrap t (Cameron, Gelbach, Miller, 2008) with 1000 repetitions.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$