Technology Adoption in Education: Usage, Spillovers and Student Achievement *

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Previous research shows that that providing detailed information to parents about their child's academic performance can significantly improve student achievement. Many school districts accomplish this at scale via technology that places student information online, but the adoption of this technology by parents is unknown. This paper uses data from a Learning Management System operating in several hundred schools and a two-stage experiment across 59 schools to study the adoption of this technology by parents along extensive and intensive margins, as well as spillovers and effects on student outcomes. A quarter of parents ever use this technology; adoption follows an S-shape; significant spillovers occur along intensive but not extensive margins; and student grades improve as a result.
JEL Codes:

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I Introduction

New technologies in the public sector often aim to improve the quality of government-provided services. This is true in the education sector, where the purchase of technologies may improve curriculum delivery, data management and school-to-parent communication. A number of papers have studied the educational impacts of information technologies such as computers (Machin et al., 2007; Barrera-Osorio and Linden, 2009; Malamud and Pop-Eleches, 2011; Fairlie and Robinson, 2013; Vigdor et al., 2014; Beuermann et al., 2015), access to the internet (Goolsbee and Guryan, 2006; Belo et al., 2013; Bulman and Fairlie, 2015), computer-aided instruction (Angrist and Lavy, 2002; Rouse and Krueger, 2004; Barrow et al., 2009; Banerjee et al., 2007; Linden, 2008; Taylor, 2015) and mobile devices in schools (Fryer, 2013; Bergman, 2014; Beland et al., 2015).

Similar to many other contexts however, the end users of education technologies may be distinct from the administrators in control of procurement. For instance, while the end users for local education agencies are often teachers, parents and students, many purchasing decisions are made at the district or school level. Given the growing private-sector investments in new education technologies—from $350 million in 2009 to $1.3 billion in 2013—an important question is whether the products purchased by local education agencies are adopted by their end users and are effective in practice (Shieber, 2014).

This paper studies the adoption, diffusion, and effects of one type of technology that has received significant private-sector investments: school-to-parent communication technologies.[1] This paper also studies several determinants of adopting this technology: peers, social comparisons and uncertainty about the potential returns to adoption. Peers may affect adoption and usage through social learning and social norms (cf. Foster and Rosenzweig, 2010). A number of papers show how peers influences can either encourage or discourage the adoption of health and agricultural-related technology, particularly in lower-income countries (Fos-

[1] For example, *Remind*, a free text-messaging platform that allows teachers to text message parents, has raised more than $59 million dollars in funding (Merced, 2014).

ter and Rosenzweig, 1995; Kremer and Miguel, 2007; Conley and Udry, 2010; Duflo et al., 2011; Oster and Thornton, 2012; Dupas, 2014). Several other papers find that information on social comparisons can "nudge" the adoption of new behaviors in a variety of contexts (Cialdini et al., 2006; Goldstein et al., 2007; Allcott, 2011; Allcott and Rogers, 2014). This paper contributes to this literature by studying how peer effects and social comparisons can affect the adoption of an education-related technology in the United States.

Previous research suggests school-to-parent communication technologies could address significant information asymmetries that exist between parents and their children—information asymmetries that can impede human capital investments (Akabayashi, 2006; Bergman, 2014; Bursztyn and Coffman, 2012; Cosconati, 2009; Hao et al., 2008; Weinberg, 2001). Recent experimental evidence shows that reducing these asymmetries can improve student achievement, and often at low cost. For instance, Kraft and Dougherty (2013) conducted an experiment in a Boston charter school that shows daily phone calls home to parents from their child's teachers improve student behaviors. Bergman (2014) randomized the provision of bimonthly text messages to parents detailing their child's missing assignments and grades, which increased student effort and achievement. Kraft and Rogers (2014) show that messages from teachers to parents significantly reduce dropout from a high school credit recovery program. Finally, Bergman et al. (2014) find that notifying parents their child has an upcoming exam through text messages improves test scores by almost a tenth of a standard deviation.

Many school districts are leveraging Learning Management Systems (LMS) to improve parental access to student information by placing students' academic data onto a "parent portal" for parents to view online. This technology allows parents to view performance indicators such as their child's grades, attendance and missing assignments in real time as teachers update it. Figure 1 shows an example of the parent portal studied in this paper. Parents are provided a website address, a user name and a password either by teachers or the school. Once a parent logs in, they see their child's classes, teachers and the associated grades. Parents may also receive and respond to messages directly from teachers as well. Figure 2 displays the screen a parent sees once they click on a specific class their child is taking. Parents can then view their child's assignments, assignment scores, the grading scale and scoring codes.

However, these systems are typically purchased at the school or district level, and the adoption and effects of this technology are unknown. As opposed to the experimental evidence on school-to-parent communication described above, which *pushes* information out to families via text messages and phone calls, this parent-portal technology requires much more of a *pull*. There are several physical and behavioral barriers to adoption and usage: parents must have internet access, be aware the system exists, keep track of their user name and password, and remember to log in. Like many school-to-parent communication systems, parent user names and passwords must be downloaded from the LMS and distributed to parents. This distribution can occur by mail, email, or at school events.

To examine adoption, diffusion, and efficacy, I use data from a learning management company operating in 15 school districts as well as a two-stage experiment providing families their account information in 59 schools across three districts. This design experimental design is similar to that used by Duflo and Saez (2003) to study the role of social interaction in retirement plan decisions: First, schools were randomized to either have a sample of families treated or to have no families treated. Second, families within treated schools were randomly selected to actually receive the intervention. In general, the influence of peers on individuals' behaviors is difficult to estimate due to the reflection problem (Manski, 1993). This design permits analysis of the intervention along extensive (whether a parent ever used the portal) and intensive margins (how often the parent used the portal).

The script providing families their account information was also randomized; in one instance stating that many other parents use the system, and in another instance stating that research shows information on academic progress can improve student performance. As a measure of parental demand for information technologies, parents were subsequently asked whether they would like to provide their email address or phone number to be used for possible future text and email-based systems designed to inform parents of their child's academic progress.

I find that parent adoption of this technology follows a typical S-shape curve over the course of the school year. Across several hundred schools, 24% of parents have ever logged into the system by the end of the year and roughly 4% of parents log in at least once per week. School-level adoption rates positively correlate with measures of family income, school-level test scores and teacher usage. At the individual level, families with higher-achieving students adopt. These patterns suggest that these technologies, without intervention, may not address the disparities in student achievement or school-to-parent communication that exist across income and performance groups (Bridgeland et al., 2008).

The experimental intervention significantly increased adoption and usage among treated families relative to families in schools where no one received the intervention. The spillover group—families who did not receive the intervention but whose children were in the same school as those who did—experienced no spillovers on adoption rates. However, families who had used the system previously did increase the intensity of their usage. Interestingly, there is evidence of additional spillovers in terms of *student* usage of the system that implies total usage was nearly equivalent across treated and spillover groups. Moreover, the randomized phone script indicates that parental demand for school-to-parent information technology increases significantly when told about the potential efficacy of the parent portal technology, and there is some evidence they respond to social norms as well.

Lastly, access to the portal system improved student grades. For both the treatment and spillover groups, GPA improved by roughly 0.10 points. Overall, the results suggest this technology can improve student outcomes, but adoption is not widespread without intervention.

The rest of this paper is organized as follows. Section II describes the data and patterns of usage. Sections III and IV present the data and empirical strategy for the experimental intervention as well as the results. Section V examines the determinants of demand for school-to-parent communication technologies and Section VI concludes and provides a cost analysis.

II Data and Descriptive Results

This study draws data from several sources. The first is deidentified data from a Learning Management System (LMS) company for the 2012-2013 and 2013-2014 school years. This LMS provider hosts a parent portal, a teacher gradebook, and a student portal. The student portal shows the same academic information to students as the parent portal shows to parents, but the user name and password are distinct from the parent user name and password.

The LMS records parent, student and teacher logins into each of these services by date. During the 2012-2013 school year, there are more than 25,000,000 login-by-day observations across all students and more than 3,000,000 logins-by-week observations across 149,107 students. The LMS also records student grades by marking period and course. Students in elementary school do not receive letter grades, so these marks are excluded from the analysis sample (9.75% of marks). Two of three districts use the LMS to record their transcript grades while the third district uses a second system to enter final grades onto student transcripts.

While the data have the unique aspect of recording portal usage and student grades, the data have several limitations as well. First, the LMS data only have a single demographic variable that is recorded across all schools, which is student gender. Second, grade levels for students are missing. Third, there are no standardized test scores in the data.

I supplement the LMS data with information from the NCES Common Core Data, which records school-level characteristics for the universe of public schools in the United States. These data describe, at the school level, demographic shares by race, receipt of free/reduced-price lunch, as well as Title I status and location in an urban, suburban, town or rural location.

Lastly, to obtain a unified measure of academic performance across school districts, I draw on the decile performance ratings constructed by GreatSchools, a nonprofit organization. GreatSchools formulates these ratings by calculating the average share of students who are proficient in math and English per grade and averaging these shares across the grades a school offers. GreatSchools then uses this measure to assign schools their state-wide decile. Thus if a school receives a rating of 10, that school is in the top-ten percent of the state according to this measure of proficiency. This variable is only used as a covariate.

Table 1 presents summary statistics of the data used to describe parent portal usage. There are 262 schools across 15 school districts. These schools enroll 149,107 students. On average, schools are 77% white, 16% Black, and 5% Hispanic. The majority (55%) receive free or reduced-price lunch. The plurality of the sample is rural (43%) with the remaining sample primarily urban and suburban. While this geographic balance is not representative of the nation, it nonetheless has significant enough variation to find informative correlates of portal adoption and usage across a variety of contexts.

The vast majority of parents have never logged into their parent portal accounts. Table 2 uses data from the LMS to describe basic usage patterns. During the 2012-2013 school year, the share of families who had ever logged into the system was 24%. Overall, 2% of families log in once per day and parents log in .13 times per week for a total of 13 times over the year on average. Conditional on ever logging in, parents log in 52 times on average. Figures 3 and 4 show the distribution of total usage for all parents and parents who have logged in at least once, respectively. The latter subgroup is important because it defines those parents who likely knew their account information at one point.

Figure 5 traces out the adoption curve—the share of parents who have ever used the parent portal—by date over the course of 2012-2013 school year. Adoption takes on an "S" shape, similar to that found in the adoption of other types of products and technologies (Rogers, 2010). There is a sharp rise at the start of the school year, but by late November the curve levels off. The share of parents who have ever logged into the system reaches just under 25% by the end of the school year. This level of adoption is not necessarily unique to this system. New York City Department of Education officials stated that many parents had never logged on to their now-defunct ARIS parent portal system. Internal analyses provided by a large California network of charter schools also showed similar levels of usage across.

Adoption also correlates with income and test scores. Figure 6 shows a negative correlation between the share of students receiving free or reduced price lunch and the share of parents who have ever logged in. Figure 7 uses the decile-proficiency measure to chart the relationship between test scores and the share of parents who have ever logged in. For the highest-performing ten percent of schools, roughly half of parents have ever logged into the system. For the lowest-performing ten percent of schools, less than ten percent of parents have ever logged into the system.

To study how usage correlates with achievement at the individual level, I run the following regression:

$$Percent_i = \alpha + \sum_{k=1}^{K} \beta_k * 1[logins \in [a_k, b_k)] + \varepsilon_i$$

In which $Percent_i$ is the average percent grade of student i. β_j are coefficients on indicator variables for whether a parent has logged in between a_k and b_k times, where the latter take on values such as one to four times or five to ten times. Zero logins is the omitted category.

Figure 8 plots the β coefficients of this regression. This graph shows the percentage-point gain in student grades associated with different levels of portal usage relative to the average percent grade of students whose parents have never logged into the system. For example, the first point on the graph shows that parents who logged in between one and four times had students who score four percentage points higher than students whose parents never logged in. The gradient is remarkably flat, with all associated gains in performance occurring between those whose parents never log in and those whose parents have logged in at least once; further usage is not associated with better or worse student performance.

To study the correlates of adoption rates at the school level, I estimate the following:

$$ShareAdopted_s = \gamma + X_s'\theta + \varepsilon_s$$

The dependent variable is the share of parents who have ever logged in at school s. The independent variables, X_s, also measured at the school level, are indicators for whether a school is a middle or high school, Title I status, urban, rural or suburban location, as well as variables for share Hispanic, Black, free and reduced-price lunch recipients. Average student-to-teacher ratio and total teacher logins at school s are included as well.

Table 3 presents the results of this regression for the year 2012-2013. The share Hispanic at a given school negatively correlates with adoption, possibly reflecting language barriers, though the portal can present information in Spanish. Interestingly, adoption at the high school level is lowest relative to middle and elementary school students' parents. Though cross sectional, this disparity is in line with other cross-sectional measures of parental monitoring, such as parent teacher conference attendance, which drops sharply from middle to high school (Noel et al., 2013).

The final row of Table 3 measures how the supply of information correlates with demand. The logins-per-teacher variable equals the total teacher logins to the LMS at a given school divided by the number of teachers at the school. This measure of how often teachers use the gradebook positively correlates with parent adoption of the system.[2] Higher student-to-teacher ratios, which may make it more difficult to keep grade information up to date, negatively correlates with adoption. These results highlight how the supply and demand for information are likely determined simultaneously, and the difficulty of recovering the causal effects of the technology on student outcomes. The experiment discussed below identifies the effects of adoption, spillovers and achievement impacts of this technology through an

[2]Similar measures of supply, such as the average number of teacher logins per student, also positively correlate with parent adoption.

encouragement design leveraging the fact that 75% of families have never logged in to the system.

III Experimental Design and Implementation

Experimental Design

The experimental intervention consists of a mailer and a phone call. The mailer informs families about the parent portal, that they will be called regarding the parent portal service, and provides the school phone number so parents can obtain their account information directly from the school. The subsequent phone call to parents told families their user name, password and the website URL for the parent portal. As described later, the script for this phone call was randomized.

The sample frame for the intervention is comprised of three districts operating 59 elementary, middle and high schools across two states. Within these districts, the sample was restricted to parents who had logged into the system five times or less. The latter restriction aims to target the intervention to low-usage parents while retaining 82% of all students' parents.

Figure 9 describes the treatment allocation. The assignment of the intervention was randomized in two stages. First, 29 schools were randomly selected to have a sample of families receive the intervention. The remaining 30 schools had access to the parent portal, but no parent received any form of the intervention by the researchers. Within the 29 selected schools, just under half of the parents in the sample frame were selected to receive the intervention. This allocation mechanism formed a treated group, who was assigned to receive a phone call and a mailer, a spillover group, who was in the same schools as the treated students but did not receive either a mailer or a phone call, and a control group, who attended schools in which no one was treated. School-level treatment assignment was stratified according to indicators for whether more than 25% of families had logged in at baseline, more than 50% of students had received free or reduced-price lunch, and indicators for each school's district. Importantly, all families and teachers were blinded to the study and the intervention was framed as district outreach to parents.

Data and Implementation

Data for this experiment are similar to the data studied above but with a few additions. As above, these data consist of login information by date for parents, teachers and students; student course grades; demographic information from the NCES Common Core; and GreatSchools school quality ratings. Students' GPA is standardized according to the untreated schools' mean and standard deviation.

The additional data come from the phone intervention. Phone agents captured call response rates, whether or not parents or guardians had internet access, and whether or not they were willing to provide their cell phone and email addresses to use for a future parent-school information technology system. Common Core data could be merged for 58 of 59 schools in the sample. GreatSchools school quality ratings could be merged for 54 of the 59 schools.

5,027 students' parents were assigned to the treatment group. Mailers notifying parents about the parent portal, how to obtain their account information, and the impending phone call were sent to arrive at the start of November 2013. A phone bank contacted families over the course of the second week of November, 2013. Phone contact was made with 61% of students' parents. Of these parents, 11% said they already had their account information, which may have been caused by the mailer, and nearly all remaining families took down their account information.

Empirical Strategy

The random assignment of the phone and the mailer intervention across schools, and subsequently across individuals, means that families in the treatment, spillover and control groups have comparable potential outcomes with respect to the treatments. By comparing outcomes between each group, we can estimate the impacts on the treatment and spillover groups. I estimate the impacts as follows:

$$y_{is} = \beta_0 + \beta_1 Treatschool_{is} + \beta_2 Treatschool_{is} \times Untreated_{is} + X'_{is}\Gamma + \eta_{is} \tag{1}$$

Outcomes y_{is} are login and academic outcomes at the individual level for students in school s. The $Treatschool_{is}$ variable indicates whether a student is in a school in which anyone receives the treatment. The $Untreated_{is}$ variable indicates a student who was not assigned to the intervention, though the individual may have been in a treated school. This specification implies that the β_1 coefficient is the effect of the intervention on those families who were selected to receive the treatment. The coefficient on the interaction term, β_2, therefore estimates the differential impact on the spillover group—those who were in schools with families selected for treatment. The test of significance for this coefficient examines whether the we can reject that the spillover group experienced similar effects to the treated group. The X_{is} term is a vector with school and individual-level controls as well as strata indicators. For any schools or students with missing data on independent variables, values are imputed and indicators are including for missingness. All standard errors are clustered at the school level.

Random assignment also implies we should background characteristics should be comparable across groups as well, in expectation. Table 4 shows the covariate balance across the three groups, respectively. The average GPA in the sample is 2.5, students miss 8% of their assignments, on average, and average total parent logins from the start of the school year until the second week of October is 0.4.[3] Student logins are much higher however: between the start of the school year and the second week of October, students logged in an average of 35 times. The schools are 64% white, 31% Black, and 3% Hispanic. 59% of students receive free

[3] As above, elementary school grades are removed from the sample in the calculation of GPA so that grades are averaged according to a four-point scale.

or reduced price lunch. At the individual level, there are no significant differences between the treatment, spillover and control groups. At the school level, which compares treated schools with untreated schools, there is one significant difference, share free or reduced-price lunch, at the 10% level. This difference is not unexpected given the number of significance tests. The number of schools is small relative to the number of observations however, and results will be shown with and without controls.

Figure A.1 shows endline usage plotted against Greatschools' test-score proficiency rating. One school is a significant outlier relative to the other schools. As will be shown, results *are* sensitive to the inclusion of this particular school. Therefore all results will be shown with and without this outlier. Once controls are added to the regressions, the results become much less sensitive to the inclusion or exclusion of this school. As a robustness check, I show how the results are affected by excluding each school in the sample one by one, which demonstrates that this outlier severely skews the results relative to any other school excluded from the sample.

Lastly, differential attrition across treatment, spillover and control groups could bias estimated impacts. The log in data does not indicate whether a student has left a participating district, but observing no final grades is an indicator of district attrition. Table A.1 tests for differential attrition across treatment and spillover groups by estimating equation (1), without controls, on an indicator for whether or not a student has a final grade. For both analyses with and without outliers, there is no evidence of differential attrition from the sample.

IV Results

Extensive and Intensive Margin Effects

Figure 10 shows the share of parents who have ever logged in by week for the treatment group and the control group excluding the spillover group and the outlier school. This figure shows extensive-margin effects by conditioning on those parents who had never logged into the system at baseline. The vertical red lines in the figure indicate when the phone treatment occurred. The share who have ever logged in rises sharply during this period—roughly two-percentage points above the six percent mean in the control schools. This increase along the extensive margin contrasts sharply with the effects for the spillover group. Figure 11 compares the adoption of the portal for the spillover group to the control group schools. The spillover group exhibits slightly lower adoption rates over time, though the regression results will show this effect is essentially zero.

Table 5 presents the regression results. Again, the *Treatschool* variable indicates whether a school was treated and the interaction term indicates whether the differential impact for the spillover group. The significance or not of the interaction term tests whether the differential effect is statistically significant. The first column shows the effects with no control variables (except strata indicators) and the control mean. This impact is positive but not significant and the spillover coefficient is negative but not significantly different from the treatment group. The second column adds controls for race and free-reduced price lunch shares as well as Title I status and school ratings. The coefficient on the treated students is larger and slightly more precise: a 2.4 percentage point increase. The spillover group exhibits a significantly smaller effect—essentially zero impact on adoption rates. Column three excludes the outlier and control variables and shows a similar coefficient to estimates with entire sample and controls. Finally, column four excludes the outlier school and adds control variables. Once the outlier is excluded however, the *Treatschool* coefficient is not sensitive to the addition of controls.

Students may also log in to view their grades and assignments through a separate account, user name and password. One possibility is that parents in the spillover group, not knowing their own account information since it was not provided to them via the treatment, ask their child to log in for them. Principals at participating schools suggested this occurs and may help improve engagement between parents and their children. Table 6 shows evidence that this is the case. The dependent variable in column one is an indicator variable for positive student use and zero parent usage. Relative to the treatment group, the spillover group is significantly more likely to have student usage with no parent usage. Column two shows parent usage with no student usage is significantly less likely for the spillover group, which is almost the same magnitude as the increase in student-only usage. For completeness column three examines the effects on an indicator for parent and student usage only, which are roughly in line with the previous results on adoption. Finally, the dependent variable in column four is an indicator for positive usage by either parents or students. Overall there is a seven percentage point increase for the treatment group and a 6 percentage point increase for the spillover group that is statistically indistinguishable from the treatment group's effect.

While the extensive margin is important, the intensive margin of usage may be equally important to fostering student achievement. Table 7 shows the treatment and spillover impacts on total parent logins. Column one, which includes all schools and no control variables, shows a negative, not significant treatment effect, and a small, positive spillover effect. Adding the control variables in column two, this effect increases to a 0.6 points for the treatment group over the 2.71 logins by the control group, which is statistically significant at the 1% level. Usage by the spillover group is not statistically different from the treatment group and is significantly different from zero (test not shown), which indicates significant spillovers in terms of parental usage. Column three removes the outlier and shows the results are much more stable, with and without controls, and are similar to the effects when all schools and baseline covariates are included. This check provides evidence that the outlier is skewing results when this are no baseline controls.

To analyze how much this outlier skews the effects, I re-rerun the regressions for parent logins, without control variables, 59 times. Each of these 59 regressions excludes a different school from the analysis. I then demean each treatment impact using a leave-one-out-mean so that the treatment effects center around zero. In Figure A.2 I plot the change in treatment effect relative to this mean for each regression. Only two schools out of the 59 exert significant changes on the magnitudes of the treatment effects. The most significant of these is the outlier school plotted previously. As shown in the second robustness check below, the inclusion or exclusion of the other school has no effect on the results.

As a second robustness check, and to affirm that the exclusion of any other school does not significantly alter the results, I exclude the previously identified outlier, and then re-rerun the regressions controlling for baseline usage and excluding every *other* school, one by one. These effects are not demeaned to show how the magnitudes and whether significance changes. Figure A.3 shows these results. Nearly all treatment impacts are around 0.60 and no treatment impact is below 0.40. All effects are significant at the 5% level.

Table 8 shows student logins also increase along intensive margins for the treatment and spillover groups, though the effects are significant at the 10% level. The increases for the treatment group and the spillover group are statistically indistinguishable from each other. As described above and related by principals, this increase may be the result of students monitoring their progress themselves or as a result of parents asking their children to log in for them.

Student Achievement Effects

Table 9 shows the impacts of the intervention on standardized GPA. The patterns across columns showing results with and without controls and with and without outliers are similar to previous results. Overall the effect size is roughly a .10 standard deviations. This effect is not differential by treatment or spillover group. This result is consistent with combined student and parent usage patterns along extensive and intensive margins, which is similar across treatment and spillover groups. The effect size is roughly half of the effect size found in Bergman (2014), in which information was actively pushed to parents about their child's academic performance.

Table 10 explores whether the effects on GPA vary by subgroup. For ease of presentation, the analysis is conducted with a school-level treatment indicator, which combines treated and spillover groups. There are no differences in heterogeneity between the spillover and treatment groups (results available on request). The results show there are no differential effects by baseline GPA, gender, or school-level demographic and performance characteristics.

Heterogeneity does occur appear to occur according to measures of baseline usage. Parents who used the system more at baseline saw smaller effects, though this result becomes marginally insignificant when outliers are excluded from the analysis (results available on request). The remaining results are robust: higher levels of student usage is associated with larger effects, and students whose teachers use the system more frequently also experience larger gains in GPA. A half-standard deviation increase in student usage leads to .02 standard deviation gain in GPA and a half-standard deviation increase in the average logins by a student's teachers leads to .10 standard deviation increase in GPA. A half-standard deviation increase in parent usage reduces effects by .01 standard deviations.

V Demand for Information Technologies

This section explores some of the determinants of parental demand for school information technologies. To do so, I leverage randomization in the script informing parents about their account information to examine whether parents respond to social comparisons or the potential returns to information. As described above, parents were informed that they have access to their child's grades online. Parents in the baseline group were then notified that the school would like to provide the parents their account information. In addition to the latter, two other groups of parents were told one of the following: (1) "thousands of other parents in the school district have used this service," or (2) "research shows that access to this information has a positive impact on student performance."

To assess whether these frames impact parents' demand for technologies that can keep parents informed, parents were informed that in the future, schools may be able to provide information about their child's academic progress via an email and text message service, and if they are interested in this service to please provide their email address and or cell phone number. Whether families provide this information and whether this is affected by social comparison or information on potential returns is suggestive of the determinants of parental demand for this type of information technology.

Experimental Design, Data and Empirical Strategy

This analysis uses randomization from the 4,176 unique phone numbers we dialed.[4] Students' parents or guardians were randomly assigned to either the baseline treatment, the social comparison treatment or the information on returns treatment described above. Randomization was stratified by district and whether a parent had ever logged into the system. Phone calls were conducted in waves and by phone type (land line versus cell phone).[5] Indicators for these design variables are included in the regression analyses.

The outcome of interest is an indicator variable for a family stating they are interested in the service and providing their cell phone number or their email address. This measure of parent demand is captured immediately and is plausibly unaffected by the peer effects on portal usage shown previously. A key assumption is that the capture of this information is correlated with parents' take up of school-to-parent communication technologies. Given that providing contact information would be sufficient to initiate a service via email or text message, this assumption is plausible.

In addition to data mentioned in the analyses above, we also gathered information about respondent's line type (cell phone versus land line) and access to the internet for those who completed the survey. 70% of respondents indicated they have internet access at home. Table 11 summarizes the other variables for the sample across the treatment and control groups. The treated groups have slightly lower GPAs than the control group (significant at the 10% level), though other important covariates appear balanced, including phone type,

[4]Families with siblings in the same school were only contacted once, so this number is fewer than the total possible number of students whose families we attempted to reach.

[5]Whether a caller is reached on their cell phone or land line depended on the phone number provided by the school districts to reach the parent if the family had both a cell phone and a land line.

parent logins, student logins and response rates. The results do not change with the inclusion or exclusion of baseline GPA.

Results

The first column of Table 12 shows the effects of the social comparison treatment and the returns treatment on apparent parental demand for a school-to-parent communication technology. Mentioning research on the potential returns to school-to-parent communication significantly increases apparent demand, as indicated by a 3.5 percentage point (21%) increase in the likelihood a parent provides their cell phone number or email address. The effect of the social comparison treatment is positive and not significant (p-value<.20).

Column two presents the results with additional covariates in the regression. The standard errors on the social comparison and information on returns decrease by 20% and the social comparison treatment coefficient becomes marginally significant. The correlates of the demand measure are also of note: Parents with internet access are significantly more likely to express interest. Baseline GPA is negatively correlated with apparent demand, suggesting that parents of higher-achieving students feel less compelled to invest in new monitoring technologies, perhaps because their child is already high performing or because the parent is already capable of monitoring their child effectively. Similarly, baseline parent usage is negatively correlated with take up as is baseline student usage; both of these results are significant at the 10% level.

The results suggest that parents may be uncertain about or understate the importance of access to information. This interpretation would be in line with previous research suggesting that parents have upwardly-biased beliefs about their child's performance (cf. Bergman, 2014; Dizon-Ross, 2014). The evidence for a social comparison effect is weaker, but suggestive enough to warrant future research as a possible determinant of parental demand. In both specifications above, the treatment coefficients are jointly significant and statistically indistinguishable from each other at conventional levels.

VI Conclusion

Previous research has shown that school-to-parent communication can improve parental monitoring and a range of student outcomes. This paper documents some of the first evidence on parents' adoption of a school communication technology that aims to scale school-to-parent communication: parent information portals. Adoption is not widespread; three quarters of parents have never logged into the system. Schools with higher log in rates tend to be higher income and higher performing, indicating that, without intervention, this technology may not close achievement gaps by income and initial test score performance.

Nonetheless, a simple intervention providing parents their account information significantly increased adoption and usage. Interestingly, there were significant usage spillovers even to parents who did not receive the intervention. This increase in usage led to higher grades in both treated and spillover group parents' children. A second experiment shows that parents respond to information about the effectiveness of this parent portal technology and there is weaker evidence that parents respond to information about the share of families already using this technology. These results are evidence that simple "nudges" can increase adoption and usage, and student grades also improve as a result of the intervention. Though test scores are not available in this data set, grades are nonetheless a powerful predictor of student performance. A number of paper show the high school grades are a stronger predictor of college performance than standardized test scores (Rothstein, 2004; Hiss and Franks, 2014; Scott-Clayton et al., 2014). These effects effects were particularly large for schools in which teachers used the system more regularly as well.

Moreover, the intervention was low cost. The mailers cost \$0.70 to print and send across two states. The phone calls cost \$1.36 per student to manage and implement. Under significant time constraints, both interventions were set up in less than two weeks, including the time to gather contact information, design mailers and script phone calls.

Overall, these results indicate both the promise and pitfalls of these technologies. Merely providing access to information online may not be enough in low-income area schools and low-performing schools. However, simple low-cost interventions can complement the implementation of new technologies and promote student achievement.

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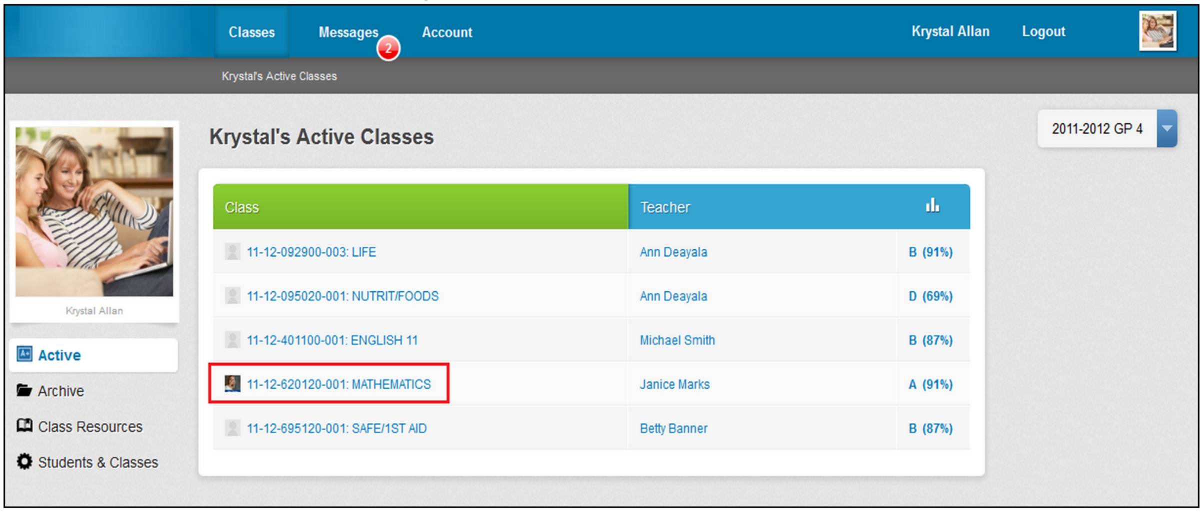
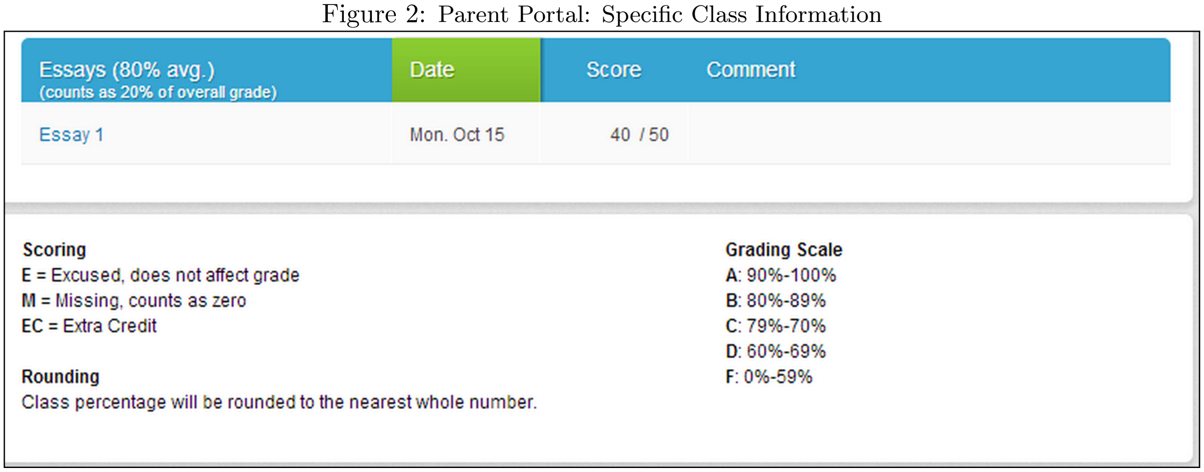
Figure 1: Parent Portal: Main Screen



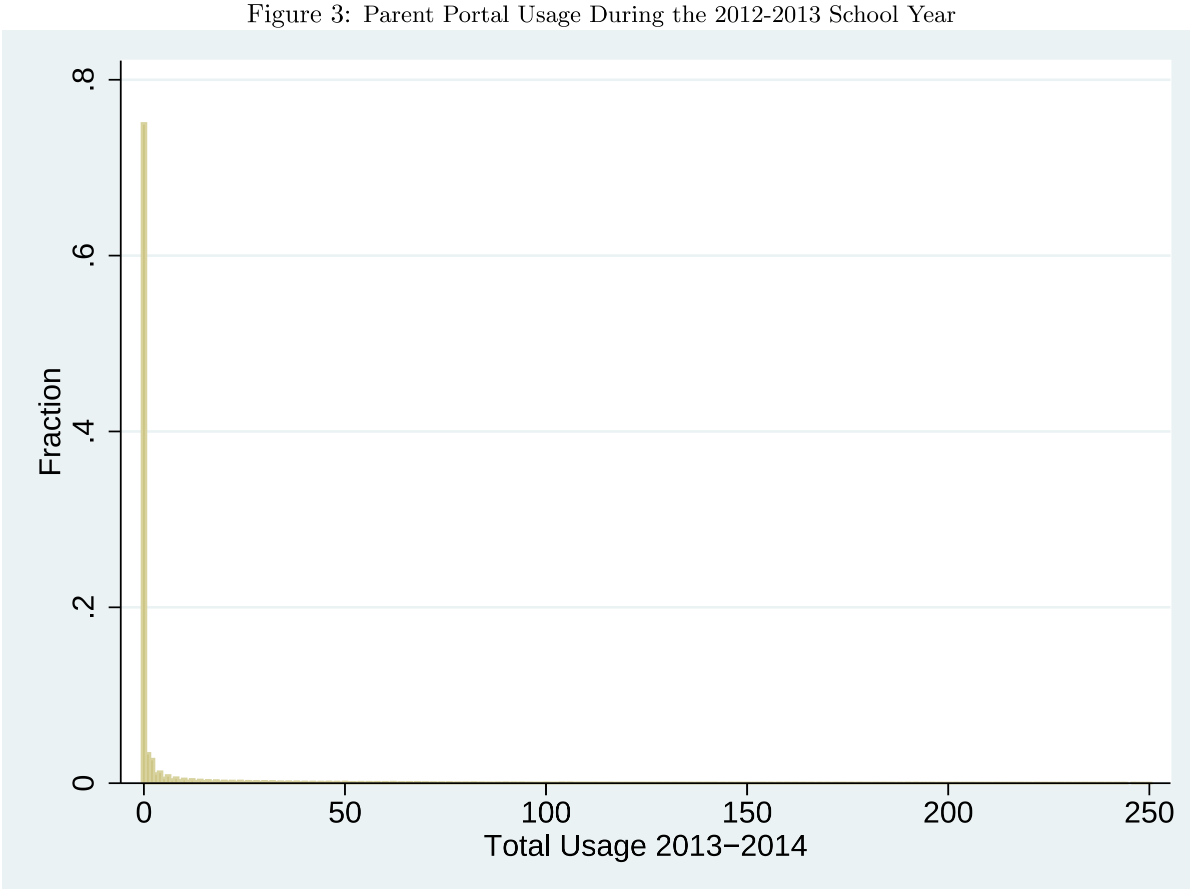
The figure shows an example of the type of academic information that can be found on parent portal. All information on this figure is fictional.

Figure 2: Parent Portal: Specific Class Information



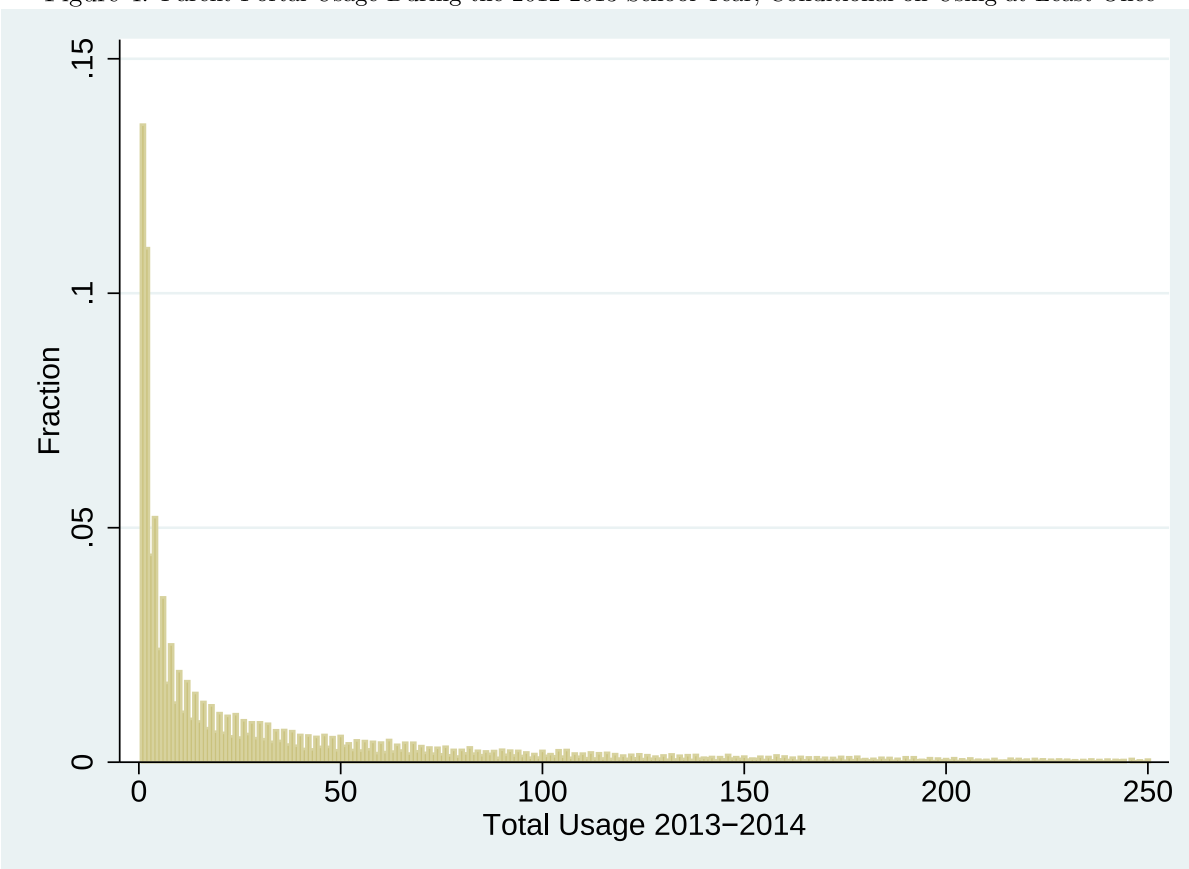
The figure shows an example of the type of academic information that can be found on parent portal once a parent clicks on a specific class. All information on this figure is fictional.

Figure 3: Parent Portal Usage During the 2012-2013 School Year



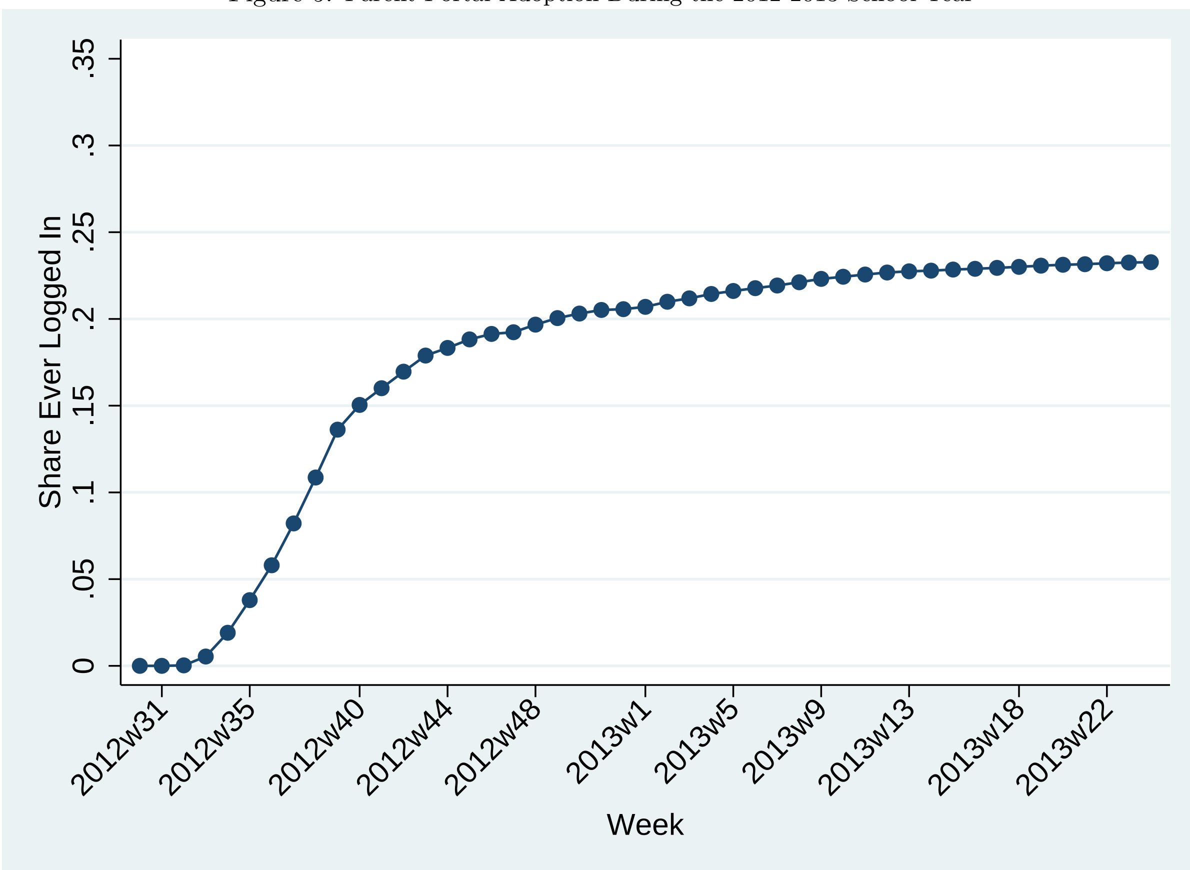
The figure shows the distribution of portal logins during the 2012-2013 school year. This figure is constructed using data from the Learning Management System and trims the top-most percentile from the data.

Figure 4: Parent Portal Usage During the 2012-2013 School Year, Conditional on Using at Least Once



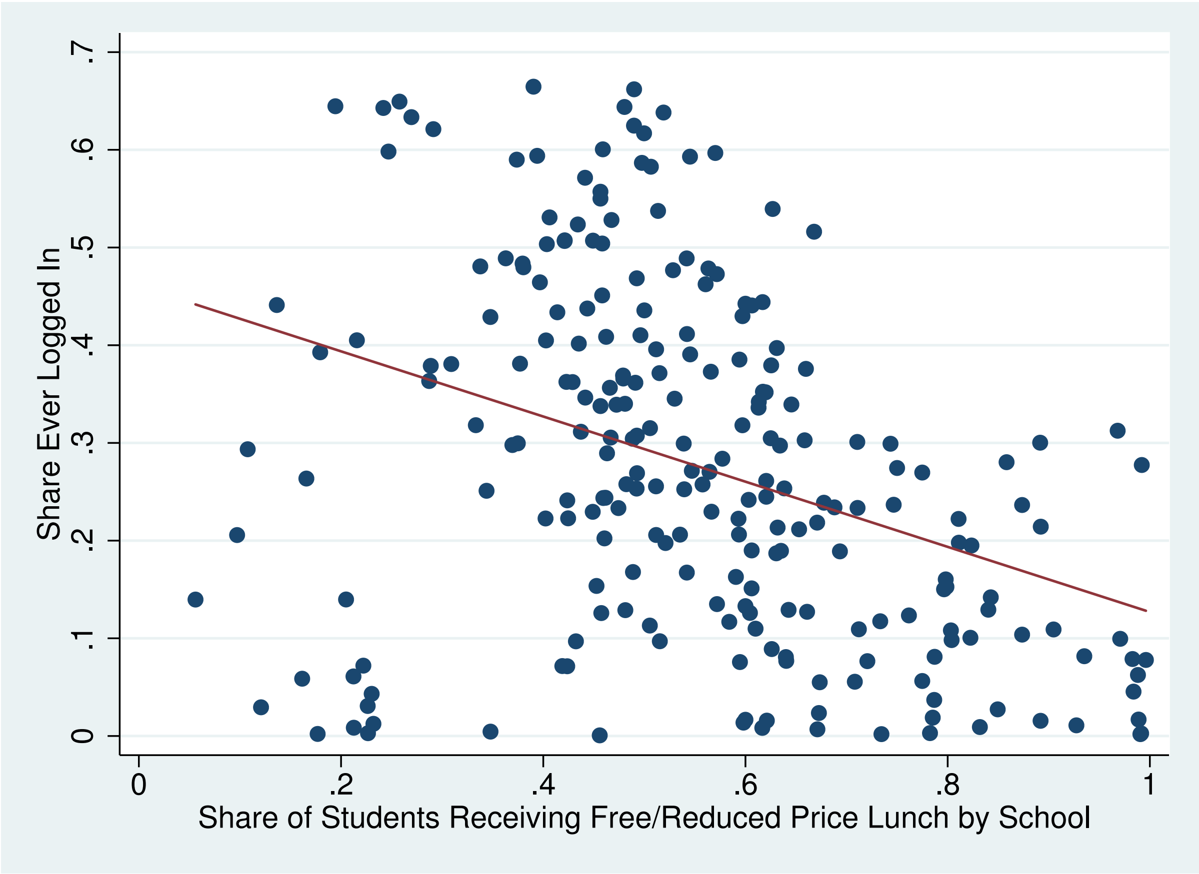
The figure shows the distribution of portal logins during the 2012-2013 school year conditional on logging in at least once. This figure is constructed using data from the Learning Management System and trims the top-most percentile from the data.

Figure 5: Parent Portal Adoption During the 2012-2013 School Year



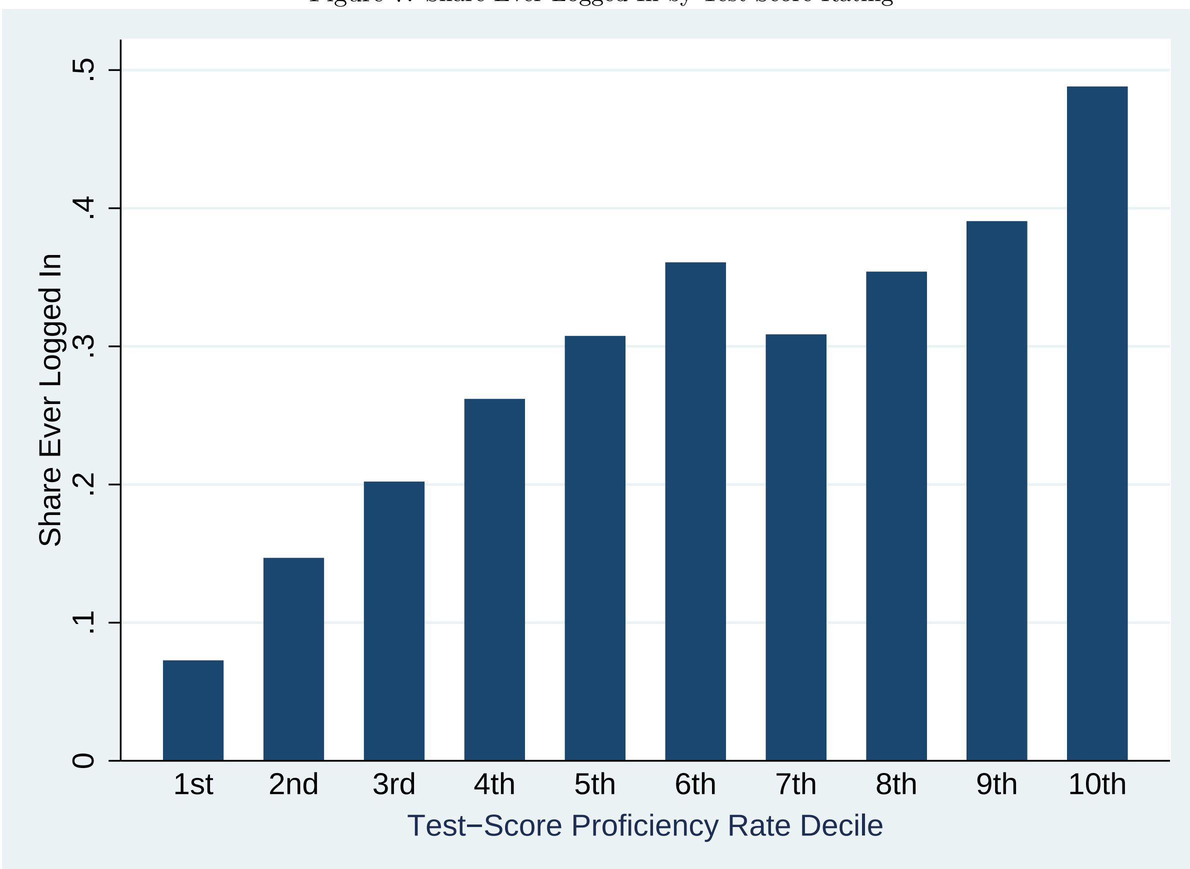
The figure shows the share of parents who have ever logged into the parent portal during the 2012-2013 school year. This figure is constructed using data from the Learning Management System.

Figure 6: Share Ever Logged In by Share Free/Reduced Price Lunch



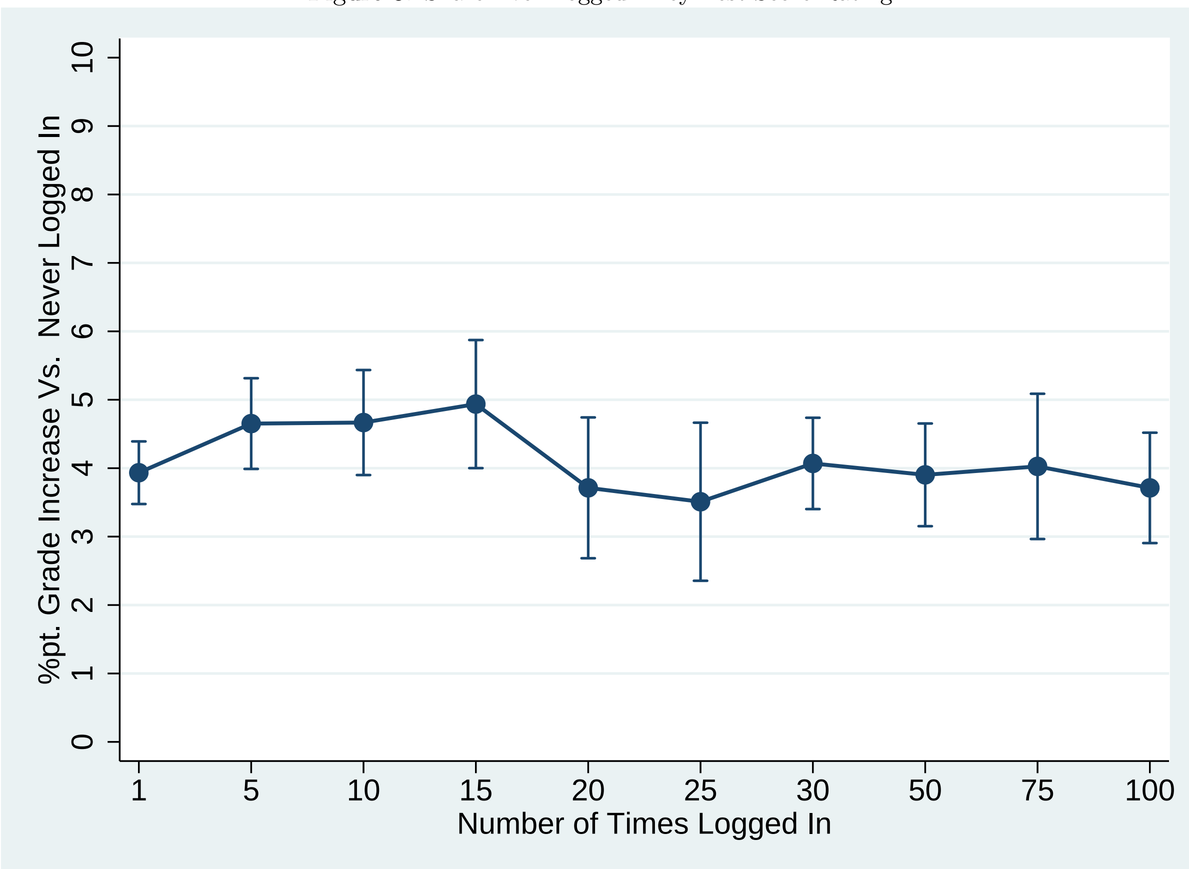
The figure shows the share of parents who have ever logged into the parent portal plotted against the share of students who receive free/reduced price lunch in each school. This figure is constructed using data from the Learning Management System.

Figure 7: Share Ever Logged In by Test-Score Rating



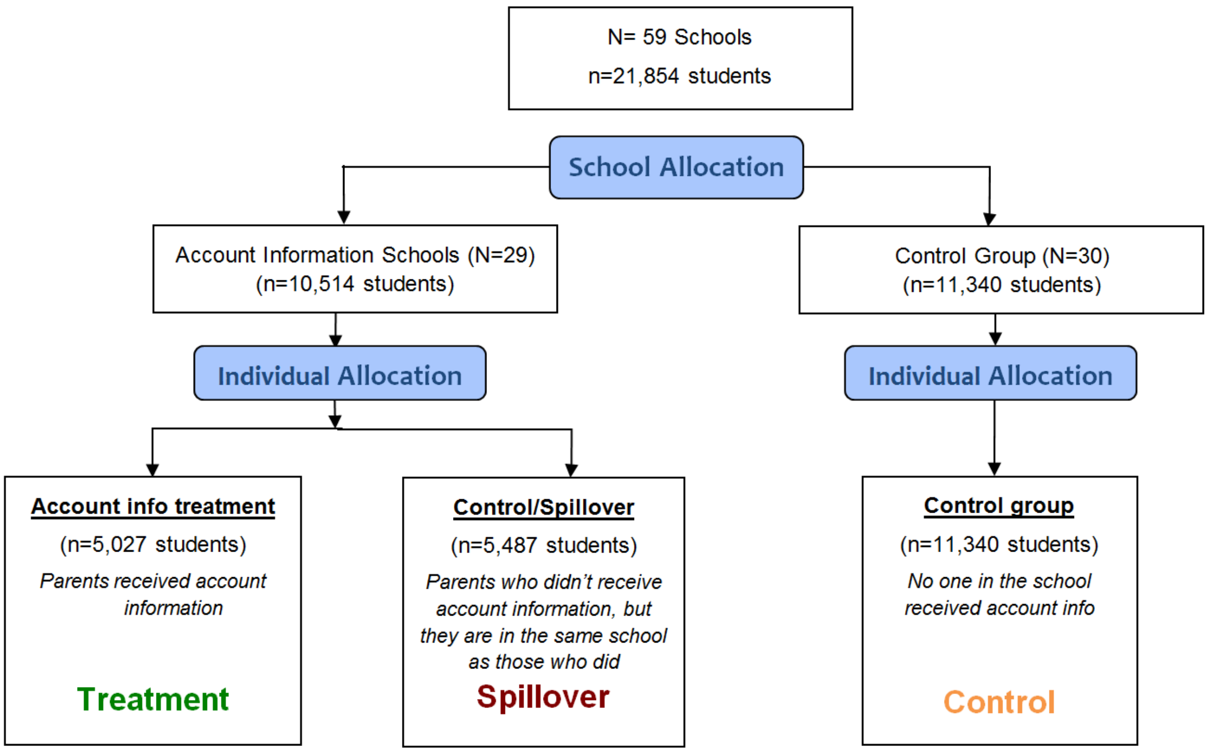
The figure shows the share of parents who have ever logged into the parent portal according to the GreatSchools Rating of each school. This figure is constructed using data from the Learning Management System.

Figure 8: Share Ever Logged In by Test-Score Rating



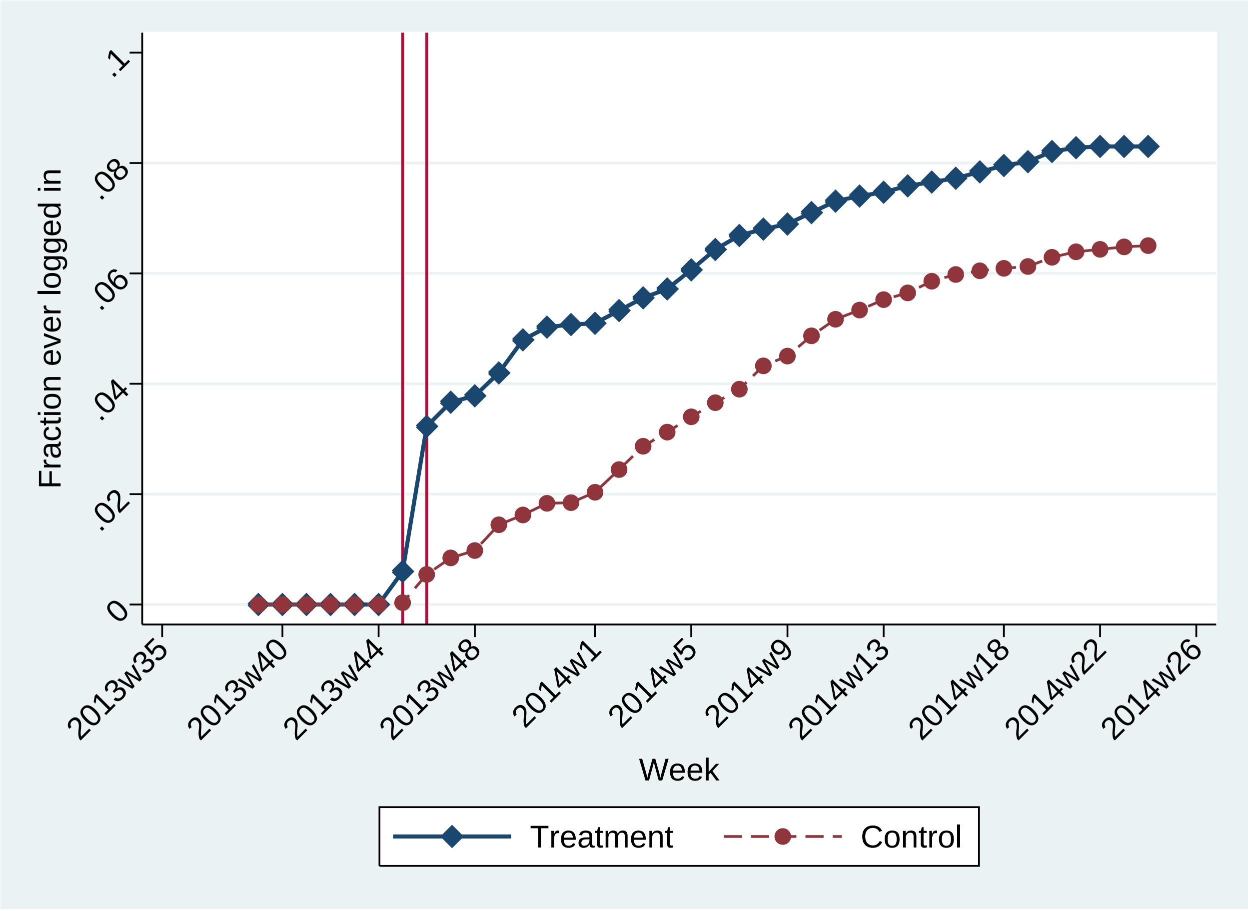
This figure shows the percentage-point gain in student grades associated with different levels of portal usage relative to the average percent grade of students whose parents have never logged into the system. This figure is constructed using data from the Learning Management System.

Figure 9: Experimental Design



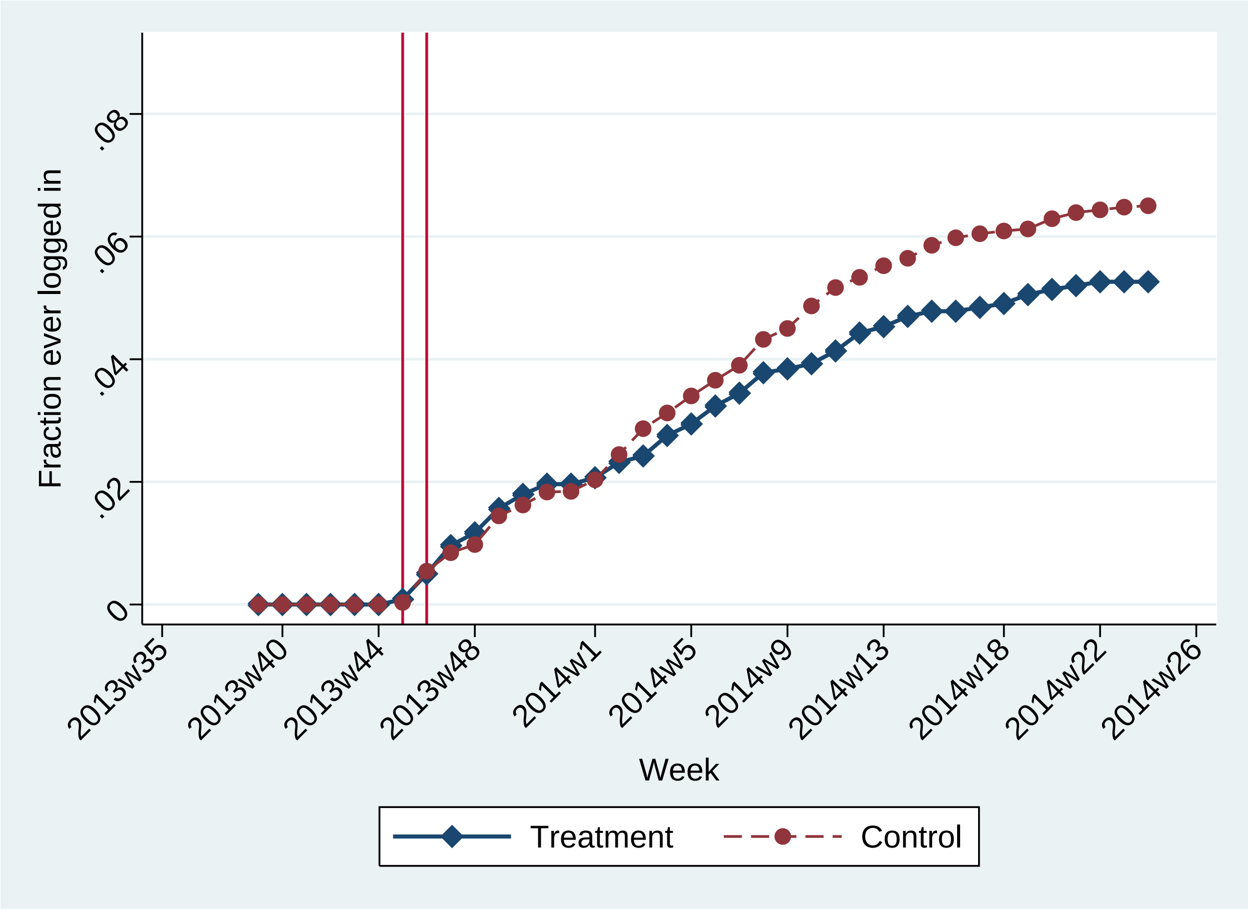
This figure shows the experimental design for the account-information intervention. Randomization occurs first at the school level and then at the student level.

Figure 10: Adoption: Treatment v. Control



This figure shows the share of parents who ever logged into the portal by week. Data come from the LMS company.

Figure 11: Adoption: Treatment v. Control



This figure shows the share of parents who ever logged into the portal by week. Data come from the LMS company.

Table 1: District Summary Statistics

Variable	Mean	Observations
Districts	N/A	15
Schools	N/A	262
Students	N/A	149,107
Female	49%	149,107
Share Hispanic	5.2%	251
Share Black	16.2%	251
Share White	77.5%	251
Share Free/Reduced Lunch	54.5%	249
Urban	21.5%	251
Suburb	20.7%	251
Town	15.1%	251
Rural	42.6%	251

This table describes school characteristics for the descriptive study. The upper four rows use data from the Learning Management System. The remaining rows use data from the NCES Common Core Data set.

Table 2: Parent-Portal Usage Information: 2012-2013

Variable	Mean	Observations
Share ever logged in	24.3%	149,107
Share who log in per day	1.7%	25,792,800
Average Logins per week	0.13	3,439,040
Average Total logins	13.29	146,060

This table describes school characteristics for the descriptive study. These numbers are constructed using data from the Learning Management System.

Table 3: School-Level Correlates of Adoption

Dependent variable		Ever Logged In	
Black	-0.058	Hispanic	-0.229**
	(0.051)		(0.113)
Middle School	0.027	High School	-0.149***
	(0.028)		(0.028)
Share Free/Reduced Lunch	-0.045	Title I	-0.045*
	(0.090)		(0.027)
Urban	0.060*	Suburban	0.055*
	(0.036)		(0.033)
Rural	0.029	Test Scores	0.026***
	(0.029)		(0.005)
Student/Teacher	-0.005***	Logins/Teacher (thousands)	0.036***
	(0.000)		(0.012)
Observations	249		
R-squared	0.55		

This table presents results from a regression of the school-level share of parents who have ever logged into the parent portal on school-level demographic and performance indicators. Robust standard errors in parentheses.

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

Table 4: Balance Table

	Treatment Mean	Control Mean	T−C	P-value	N	Obs.
Treatment v. Control						
GPA	2.44	2.48	-0.05	0.50	59	15,192
Fraction Missing	0.08	0.07	0.01	0.65	59	16,174
Parent Logins	0.41	0.42	-0.01	0.29	59	16,367
Student Logins	38.2	34.6	3.70	0.61	59	16,367
Spillover v. Control						
GPA	2.44	2.48	-0.04	0.53	59	15,680
Fraction Missing	0.08	0.07	0.01	0.64	59	16,639
Parent Logins	0.44	0.43	-0.00	0.71	59	16,827
Student Logins	37.3	34.9	2.36	0.74	59	16,827
School Level						
White	0.63	0.65	-0.02	0.45	58	N/A
Black	0.34	0.30	0.04	0.23	58	N/A
Hispanic	0.02	0.03	0.01	0.42	58	N/A
Fraction FRL	0.63	0.57	0.06	0.09	58	N/A
Rating	4.5	4.9	-0.40	0.34	54	N/A

All data are at the student level and are constructed from the learning management company data, with the exception of variables under the "School Level" heading, which are from the NCES Common Core Data and are school-level aggregate variables. Standard errors clustered at the school level are shown in parentheses.

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

Table 5: Treatment and Spillover Effects on Adoption

Dependent variable	Ever Logged In			
Treatschool	0.014	0.024**	0.025**	0.025**
	(0.011)	(0.009)	(0.010)	(0.010)
Treatschool×Untreated	-0.027	-0.027**	-0.028**	-0.027***
	(0.005)	(0.005)	(0.005)	(0.005)
Control mean	0.07		0.065	
Observations	18,429	18,429	17,891	17,891
Controls	No	Yes	No	Yes
Outliers Excluded	No	No	Yes	Yes

All data are at the student level and are constructed from the learning management company data. Standard errors clustered at the school level are shown in parentheses.

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

Table 6: Treatment and Spillover Effects by Parents and Students

Dependent variable	Student Use Only	Parent Use Only	Parent & Student Use	Parent or Student Use
Treatschool	0.051	-0.009	0.026**	0.072**
	(0.032)	(0.009)	(0.011)	(0.032)
Treatschool×Untreated	0.014*	-0.012**	-0.015***	-0.010
	(0.007)	(0.004)	(0.006)	(0.007)
Control mean	0.503	0.051	0.095	0.675
Observations	21,854	21,854	21,854	21,854
Controls	Yes	Yes	Yes	Yes
Outliers Excluded	No	No	No	No

All data are at the student level and are constructed from the learning management company data. Standard errors clustered at the school level are shown in parentheses.

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

Table 7: Effects on Parent Usage

Dependent variable	Total Parent Logins			
Treatschool	-0.275	0.576***	0.571**	0.569***
	(0.656)	(0.202)	(0.278)	(0.202)
Treatschool×Untreated	0.057	-0.171	-0.002	-0.163
	(0.213)	(0.223)	(0.212)	(0.220)
Control mean	2.71		2.17	
Observations	21,854	21,854	21,453	21,453
Controls	No	Yes	No	Yes
Outliers Excluded	No	No	Yes	Yes

All data are at the student level and are constructed from the learning management company data. Standard errors clustered at the school level are shown in parentheses.

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

Table 8: Effects on Student Usage

Dependent variable	Total Student Logins			
Treatschool	8.13	5.80*	10.9*	5.82*
	(6.01)	(3.27)	(5.94)	(3.27)
Treatschool×Untreated	-0.153	-0.171	-0.304	-0.162
	(0.763)	(0.223)	(1.13)	(0.764)
Control mean	44.5		44.0	
Observations	21,854	21,854	21,453	21,453
Controls	No	Yes	No	Yes
Outliers Excluded	No	No	Yes	Yes

All data are at the student level and are constructed from the learning management company data. Standard errors clustered at the school level are shown in parentheses.

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

Table 9: Effects on Student GPA

Dependent variable	Grade Point Average Z-Score			
Treatment	0.080	0.098**	0.124	0.114**
	(0.087)	(0.048)	(0.084)	(0.049)
Treatschool×Untreated	-0.007	0.005	-0.010	0.004
	(0.021)	(0.017)	(0.021)	(0.017)
Observations	19,218	19,218	18,878	18,878
Controls	No	Yes	No	Yes
Outliers Excluded	No	No	Yes	Yes

All data are at the student level and are constructed from the learning management company data. GPA standardized according to control-group means. Standard errors clustered at the school level are shown in parentheses.

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

Table 10: Subgroup Effects on Student GPA

Dependent variable	Grade Point Average Z-Score							
Treatschool	0.126	0.107**	0.135*	-0.015	0.171	0.107**	0.072	-0.129*
	(0.116)	(0.045)	(0.068)	(0.141)	(0.121)	(0.046)	(0.046)	(0.065)
Treatschool×Base GPA	-0.010							
	(0.043)							
Treatschoo×Female		-0.013						
		(0.022)						
Treatschool×Share Black			-0.113					
			(0.114)					
Treatschoo×Share Reduced-Price Lunch				0.214				
				(0.218)				
Treatschool×GS Rating					-0.013			
					(0.024)			
Treatschool×Base Usage						-0.008*		
						(0.004)		
Treatschool×Student Base Usage							0.001**	
							(0.000)	
Treatschool×Teacher Base Usage								0.001***
								(0.000)
Observations	19,218	19,218	19,218	19,218	19,218	19,218	19,218	19,218
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Outliers Excluded	No	No	No	No	No	No	No	No

All data are at the student level and are constructed from the learning management company data. GPA standardized according to control-group means. Standard errors clustered at the school level are shown in parentheses.

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

Table 11: Balance Table - Survey Experiment

	Treatment Mean	Control Mean	T−C	P-value	Obs.
Social Comparison v. Control					
Responded to all questions	0.38	0.38	0.00	0.91	2,793
GPA	2.37	2.44	-0.08	0.06	2,605
Land Line	0.45	0.42	0.03	0.11	2,793
Internet Access	0.67	0.70	-0.03	0.34	1,057
Parent Logins	0.56	0.48	0.08	0.33	2,793
Student Logins	21.0	22.4	-1.41	0.28	2,793
Research on Returns v. Control					
Responded to all questions	0.40	0.38	0.02	0.32	2,776
GPA	2.36	2.43	-0.07	0.09	2,585
Land Line	0.44	0.42	0.02	0.33	2,776
Internet Access	0.70	0.70	-0.00	0.87	1,072
Parent Logins	0.56	0.47	0.09	0.30	2,776
Student Logins	21.9	21.2	-0.67	0.62	2,776

All data are at the student level and are constructed from the learning management company data and call center information. Robust standard errors are shown in parentheses.

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

Table 12: Survey Experiment Results

Dependent Variable	Capture Rate	Capture Rate
Social Comparison	0.018	0.018*
	(0.014)	(0.011)
Research on Returns	0.035**	0.025**
	(0.014)	(0.011)
Has Internet Access		0.396***
		(0.023)
Baseline GPA		-0.010**
		(0.004)
Baseline Parent Usage		-0.004*
		(0.002)
Baseline Student Usage (×10)		-0.003*
		(0.000)
Control mean	17%	
Observations	4,176	4,176

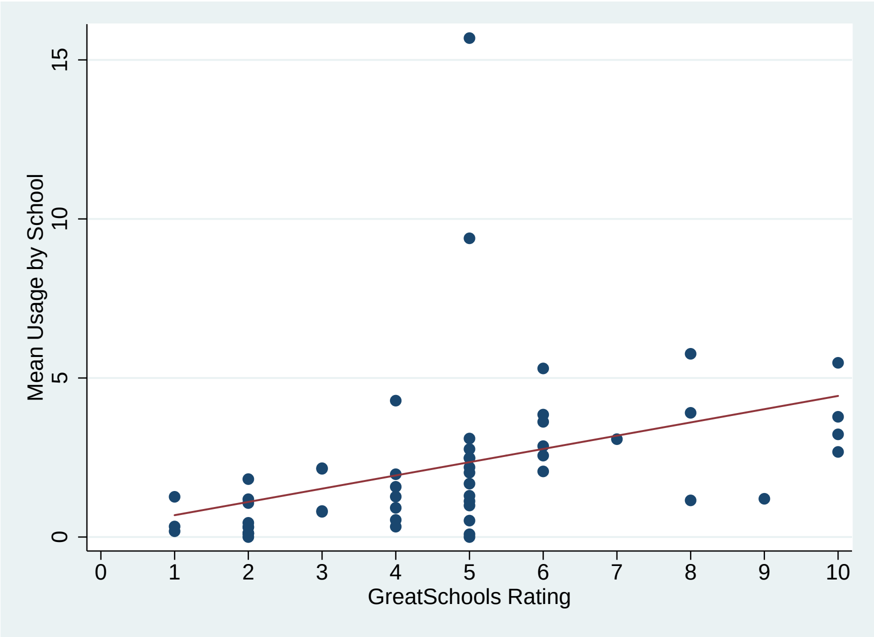
All data are at the student level and are constructed from the learning management company data. GPA standardized according to control-group means. Standard errors clustered at the school level are shown in parentheses.

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

Appendix

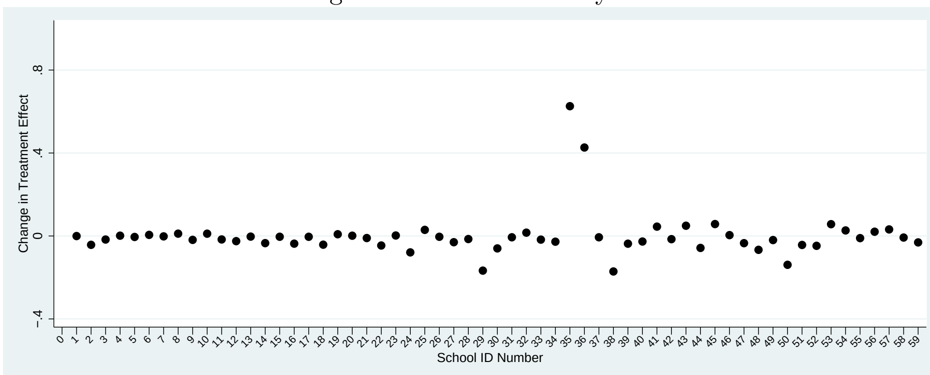
Figures

Figure A.1: Outlier Usage



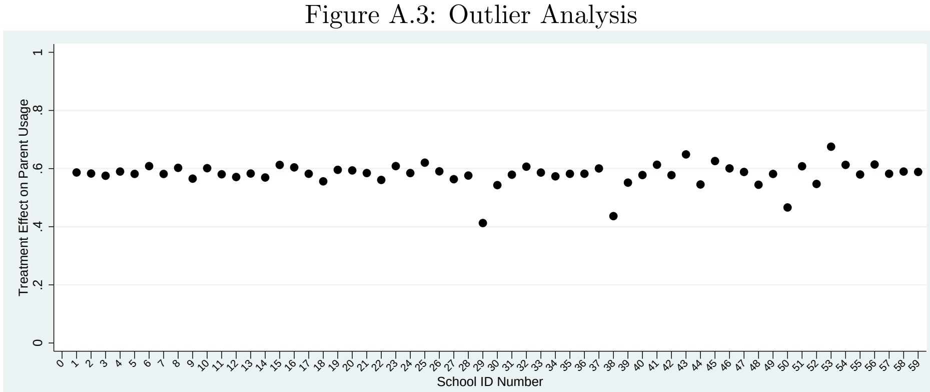
The figure shows the distribution of endline usage by GreatSchools' test-score proficiency rating with a fitted line from a regression of usage on rating.

Figure A.2: Outlier Analysis



This figure shows usage treatment effects estimated through 59 regressions with no control variables. Each regression excludes a particular school and each dot on the graph shows a de-meaned treatment effect when that school is excluded. The treatment effects are demeaned using a leave-one-out mean, so that the treatment effects center around zero. Data come from the LMS company.

Figure A.3: Outlier Analysis



This figure shows usage treatment effects estimated through 59 regressions, controlling for baseline usage to increase precision. Each regression excludes the outlier school shown in Figure A.1., and then excludes one additional school one at a time. Each dot represents the treatment effect for excluding a different school. All treatment effects are significant at the 5% level. Data come from the LMS company.

Tables

Table A.1: Attrition

Dependent Variable	Has Final Grade	Has Final Grade
Treatschool	-0.043	-0.050
	(0.041)	(0.043)
Treatschool×Untreated	0.006	0.006
	(0.006)	(0.006)
Control mean	0.83	0.82
Observations	21,854	21,453

All data are at the student level and are constructed from the learning management company data. The outcome variable is an indicator for a student having a final grade in the system. Standard errors clustered at the school level are shown in parentheses.

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