Nudging Technology Use: Descriptive and Experimental Evidence from School Information Systems*

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As schools are making significant investments in education technologies it is important to assess whether various products are adopted by their end users and whether they are effective as used. This paper studies the adoption and ability to promote usage of one type of technology that is increasingly ubiquitous: school-to-parent communication technologies. Analyzing usage data from a Learning Management System across several hundred schools and then conducting a two-stage experiment across 59 schools to nudge the use of this technology by families, I find that 57% of families ever use it and adoption correlates strongly with measures of income and student achievement. While a simple nudge increases usage and modestly improves student achievement, without more significant intervention these technologies may exacerbate gaps in information access and student performance across income and performance levels.

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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; Dettling et al., 2015), computer-aided instruction (Angrist and Lavy, 2002; Rouse and Krueger, 2004; Barrow et al., 2009; Banerjee et al., 2007; Linden, 2008; Taylor, 2015), teacher dashboards (Tyler, 2013) and mobile devices (Fryer, 2013; Bergman, 2014; Castleman and Page, 2014; York and Loeb, 2014; Beland and Murphy, 2015; Castleman and Page, 2016; Bergman and Chan, 2017; Page and Gehlbach, 2017).

Similar to many other contexts however, the end users of education technologies may be distinct from the administrators in control of procurement. 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. For instance, New York City spent $95 million on their "Achievement Reporting and Innovation System," which was subsequently ended as a result of high costs and low usage by teachers and parents, according to an agency spokesperson.[1] Given the growing private-sector investments in new education technologies, from $600 million in 2009 to $2.5 billion in the first half of 2015 alone, plus an additional $11 billion spent by K-12 and higher-education institutions (Adkins, 2016; McCarthy, 2016), an important question is how the products purchased by local education agencies are adopted by their end users and whether promoting usage impacts outcomes.

This paper studies a technology that is increasingly ubiquitous in schools: school-to-family

[1] See this article in the *The Daily News.*

communication technologies. Unlike computer-aided instructional technologies, which can substitute for teacher instruction (Taylor, 2015), communication technologies can complement instruction in the classroom by informing families about students' academic progress. These technologies also have the potential to remedy the gap in communication quality that exists between low and high-achieving schools (Bridgeland et al., 2008).

Previous research suggests school-to-parent communication can address significant information asymmetries that exist between parents and their children. These asymmetries 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 information problems 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) and Bergman and Chan (2017) randomized the provision of text messages to parents detailing their child's missing assignments and grades increased student effort and achievement. Kraft and Rogers (2015) show that messages from teachers to parents significantly reduced dropout from a high school credit recovery program and Rogers and Feller (2016) find letters to parents about their child's absences and designed using ideas from behavioral science reduce absenteeism.

Many school districts are leveraging Learning Management Systems (LMS) to improve family access to student information at scale by placing students' academic data onto an online "portal" for view online. This technology allows families 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 portal studied in this paper. Families are provided a website address, a user name, and a password either by teachers or other school employees. Once a family logs in they see the student's classes, teachers and the associated grades. Figure 2 displays the screen seen once they click on a specific class their child is taking. Families can then view their child's assignments, assignment scores, the grading scale and scoring codes. The exact same information can be viewed through a student account with a separate user name and password also for the purpose of tracking assignments and grades.

However these systems are typically purchased at the school or district level, and the adoption, usage 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 potential 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.

This paper studies the adoption of this education technology by families and whether a simple nudge can promote usage and improve student outcomes. To examine use, I analyze data from a learning management company operating in 15 school districts that tracks parent and student logins into the portal as well as student grades.

To nudge additional use, I selected a sample of low-users across three school districts and conducted a two-stage experiment informing families about the portal and providing families their account information. The experimental design is similar to that used by Duflo and Saez (2003) to study the role of social interactions in retirement plan decisions: First, schools are randomized to either have a sample of families treated or to have no families treated. Second, families within treated schools are randomly selected to actually receive the intervention, which provides sign-up information to parents via phone calls and letters. This design permits analysis of the direct effects of the intervention on usage as well as potential spillover effects.

In general, the influence of peers on individuals' behaviors is difficult to estimate due to the reflection problem (Manski, 1993). A number of papers show how peer influence can either encourage or discourage the adoption of health and agricultural-related technologies, particularly in lower-income countries (Foster and Rosenzweig, 1995; Kremer and Miguel, 2007; Conley and Udry, 2010; Foster and Rosenzweig, 2010; Duflo et al., 2011; Oster and Thornton, 2012; Dupas, 2014). Several other papers find that social norms can "nudge" the adoption of new behaviors in a variety of contexts (Cialdini et al., 2006; Goldstein et al., 2007; Gerber and Rogers, 2009; Allcott, 2011; Allcott and Rogers, 2014; Bhargava and Manoli, 2015; Hallsworth et al., 2017; Bird et al., 2017). This paper contributes to this literature by studying whether peers influence the adoption of an education-related technology in the United States.

Qualitative interviews with school administrators and parents revealed many parents use their child's student account to log in, as they can each view the same information. I report "family" usage of parent and student accounts. I find that family adoption of this technology follows an S-shape curve over the course of the school year that rises quickly then levels off. Usage is far from complete. Across several hundred schools, 25% of families have ever logged into their parent accounts by the end of the year and roughly 4% of families log into those accounts at least once per week. More families use the student accounts: 49% of student accounts have ever been used and 57% of either parents or student accounts have ever been used. School-level adoption rates positively correlate with measures of family income, school-level test scores and teacher usage. Families with higher-achieving students adopt. Importantly, these patterns suggest that this technology, without intervention, may not address the disparities in student achievement or school-to-family communication that exist across income and performance groups.

The experimental intervention increased total family usage (either to student or parent accounts) by nearly two logins per month compared to families in schools where no one received the intervention. There are significant and near-complete spillovers, which is similar to the findings in Duflo and Saez (2003).

Increasing usage modestly improved student grades. For both the treatment and spillover groups, GPA improved by 0.10 points. Though it is difficult to consider a treatment-on-the treated effect given the effects on both adoption *and* usage through multiple channels, the results suggest this technology is capable of a modest improvement in student outcomes but that usage is not widespread without significant intervention, especially among schools serving lower-income and lower-performing students.

The rest of this paper is organized as follows. Section II describes the data and patterns of usage. Sections III describes the experimental design to nudge additional usage. Sections IV presents the results of this experiment. Section V concludes and provides a basic 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 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 logins into the parent, student and teacher portals by date. During the 2012-2013 school year, there are nearly 7,000,000 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).

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. However, GPA is a stronger predictor of college performance than SAT or ACT scores, even unadjusted for high school quality (Rothstein, 2004; Bowen et al., 2009; Hiss and Franks, 2014; Scott-Clayton et al., 2014).

I supplement these 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 school performance across school districts, I draw on the decile performance ratings constructed by GreatSchools, a nonprofit organization. In most settings, 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 portal usage. There are 264 schools across 15 school districts. These schools enroll 149,107 students. On average, schools are 78% white, 15% Black, and 4% Hispanic. The majority (55%) receive free or reduced-price lunch. The plurality of the sample is rural (41%) with the remaining sample primarily urban and suburban. While this geographic balance is not representative of the United States, it nonetheless has significant enough variation to find informative correlates of portal adoption and usage across a variety of contexts.

The vast majority of families have never logged into their parent accounts. Table 2 uses data from the LMS to describe basic usage patterns. During the 2013-2014 school year, the share of families who had ever logged into the system was 25%. Overall, 8% of parents log in at least once per week and a total of 13 times during the year, on average. For student accounts, 49% had ever been used and 22% were used at least once per week for a total of 48 times during the year, on average. There is significant overlap in the usage between student and parent accounts: 57% of either account have ever been logged into.

Figure 3 shows the distribution of total usage of parent accounts for all users who have logged in at least once. The latter is important because it defines those who likely knew their account information at one point. Likewise, Figure 4 shows the same histograms for student account usage conditional on logging in at least once. All of the histograms have long right tails, though student-account usage dwarfs parent-account usage both in terms of extensive and intensive margins. Because interviews with school officials and parents found that parents use both student and parent accounts, I focus on usage of either account from here on.

Figure 5 traces out the adoption curve for either account—the share of families using either the parent portal or the student portal by date over the course of 2013-2014 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 families who have ever logged into the system reaches just under 60% by the end of the school year.

Adoption also correlates with measures of 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 families who have ever logged in. For the highest-performing ten percent of schools, roughly 75% of families have ever logged into the system. For the lowest-performing ten percent of schools, roughly 20% of families have ever logged into the system.

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

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

In which GPA_i is the average grade of student i. β_k are coefficients on indicator variables for whether a family has logged in to any account between a_k and b_k times, where the latter take on values such as 25 to 50 times or 50 to 75 times. Zero logins is the omitted category. I report the GPAs associated with each category of logins.

Figure 8 plots these predicted GPAs based on the regression above. This graph shows the average grade of students whose family has never logged into the system, followed by those who have logged in between 25 and 50 times, and so on. There is a strong correlation between logins and GPA. The most substantial association–roughly half a GPA point—occurs between logging in zero times versus 25 times or more over the course of the year.

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

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

The dependent variable is the share of families who have ever logged into any account 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. ψ_s is the residual term, and the regression weights each school observation by the number of students enrolled.

Table 3 presents the results of this regression for the year 2012-2013. The share Black at a given school negatively correlates with adoption while the coefficient on the share Hispanic is small and insignificant after controlling for the remaining covariates. Interestingly, adoption at the middle-school level is largest and statistically different from elementary and high school families' adoption. 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 shows two measures related to the potential supply of information. 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 family 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.

Overall these variables can explain nearly 70% of the variation in the adoption shares. Much of this variation appears to be explained by Title I status, the grade levels served by the school, and teacher logins. The results also 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 usage, spillovers and achievement impacts of this technology through an encouragement design.

III Experimental Design and Implementation

Experimental Design

The experimental intervention consisted of a mailer and a phone call targeted to parents. The mailer informed families about the parent portal, that they will be called regarding the parent portal service, and provided 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 if they had not already obtained it from the school.

The sample frame for the intervention was 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 ever logged into the parent portal five times or less. The latter

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

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 families 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 into the parent portal 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 a district-led outreach to parents.

Data and Implementation

The data used for this experiment are similar to the data studied above. As above, baseline data used from the LMS data consist of portal login information and student course grades. NCES 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. Students' GPA is standardized by district according to the untreated schools' means and standard deviations.

As described previously, 5,027 students' parents (4,557 unique phone numbers) 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.

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 similar potential outcomes with respect to the treatments. By comparing outcomes between each group it is possible to estimate the impacts on the treatment and spillover groups. I estimate intent-to-treat impacts as follows.[3]

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

Outcomes y_{is} are login and academic outcomes at the individual level for students in school s.[4] The $Treatschool_{is}$ variable indicates whether a student is in a school in which anyone receives the treatment. The $Spillover_{is}$ 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 spillover term, β_2, 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 provides evidence whether 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: the share white and share Black at the school, the *GreatSchools* rating of the school, the fraction receiving free or reduced-priced lunch, baseline total logins and an indicator for ever logging in. I impute any missing values with the mean value of the variable and include indicators for missing data for any schools or students lacking such data. All standard errors are clustered at the school level.

The histograms described previously show that the measures of the number of logins are

[3] Treatment-on-the-treated impacts are confounded by the simultaneous impact on additional usage by existing users and adoption by new users through their parent or student account.

[4] There are no effects on the amount of logins by teacher (results available upon request).

heavily-skewed count variables (e.g. Figure 3). As such, I model the data on logins using a negative binomial regression and report marginal effects at the means. Though not shown, results are similar in magnitude and precision to a transformation of the data as well, such as inverse-hyperbolic sine transformation;[5] results are also quite similar, though marginally less precise, when using linear regression. When the outcome is an indicator for any usage, I model the data using a linear-probability model, though average marginal effects are almost exactly the same when estimated using a Probit or Logit model.

Random assignment also implies background characteristics should be comparable across groups 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 logins into the parent and student portals from the start of the school year until the second week of October are 0.6 and 22, respectively. As in the descriptive results, Table 4 also shows that logins into the student account are much higher in the study sample.

The schools are 63% white, 30% Black, and 3% Hispanic. 60% of students receive free or reduced price lunch. At the individual level and the school level there are no significant differences between the treatment, spillover and control groups. The number of schools is small relative to the number of observations however, and results will be shown with and without controls.

Differential attrition across treatment, spillover and control groups could bias estimates of treatment effects. The login data do 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. There is no evidence of differential attrition from the sample.

[5] This transformation is akin to a log transformation though it does not treat zeros as missing.

IV Adoption, Spillovers and Efficacy

Usage Effects

Figure 10 plots the treatment effect on logins per month for the treatment group compared to the control schools. The vertical red line in the figure indicates when the phone treatment occurred. Usage immediately increases by roughly 1.5-2.5 logins per month. The treatment effect persists through the remainder of the school year, with an upward spike in March. Figure 11 shows the same graph for the spillover group. Treatment effects on the spillover group exhibit a similar pattern as the treatment: an swift rise at the outset that largely persists throughout the remainder of the academic year. The levels of the effect are slightly smaller however, but nonetheless this is an indicator of positive spillovers.

Table 5 presents the regression results. The *Treated school* variable indicates whether a school was treated and the spillover term indicates the differential impact for the spillover group. The effect on the spillover group is the *Treated school* coefficient plus the interaction-term coefficient. The significance or not of the interaction term tests whether the differential effect is statistically significant. For each outcome, the first column shows the effects with no control variables (except strata indicators and baseline usage to assess effects at the mean) and the control mean. The adjacent column presents the same outcome with the additional controls as described above.

The first two columns of Table 5 show that total usage increased by roughly 11 logins, or nearly two logins per month as a result of the intervention. The effects are smaller for the spillover group by one login in total and this difference is significant at the 10% level from the treatment group when controls are included. This indicates significant spillovers that are only marginally smaller than the effects on the treatment group. This large spillover effect is consistent with the large spillovers found by Duflo and Saez (2003) (though they need not be), which found increases in the enrollment of Tax Deferred Accounts that were statistically indistinguishable between the treatment and spillover groups.

The remaining two columns show that, by the end of the year, just over two-thirds of families had logged into either the student or parent portal. There is a four percentage point increase in the likelihood of logging into a portal. This effect is significantly smaller for the spillover group, which was not provided their account information. The latter is likely a reason why total logins are slightly smaller for the spillover group than the treatment group. In results not shown, the effects on take up are significantly larger among those who had never logged in at baseline—8 percentage points—and remain smaller for the spillover group.

The results on both adoption and usage have implications for interpreting any kind of treatment-on-the-treated effect for other outcomes. Viewing the effects as only operating through one channel or the other clearly violates the exclusion restriction as there are effects on both the intensive and extensive margins and the intervention may have affected usage by revising parents' view on the importance of monitoring their children. Overall, the reduced-form effects of the intervention shows additional usage that is equivalent to between one and two logins per month for the treatment and spillover groups.

Student Achievement Effects

This section examines the impact of the nudge intervention described in Section III on student GPA. Table 6 presents the results. The first column shows results without controls and the second column adds the controls described in the text, including baseline GPA. The latter improve the precision of the estimates significantly but the point estimate remains almost unchanged. Overall the effect size is 0.10 standard deviations and is significant at the 5% level.

The effect on student grades does not significantly differ by treatment or spillover group. This result is consistent with the effects on total logins patterns, which are similar for both 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 rather pulled from a portal system. As stated above, it is difficult to scale this effect through an instrumental-variable strategy that uses the intervention as an instrument for usage; the exclusion restriction is not satisfied as adoption, usage and potentially awareness about the importance of monitoring and information may all have been affected by the intervention. Nonetheless, the results do highlight the potential for a low-cost intervention to leverage this technology to promote academic achievement.

Table A.2 shows exploratory analyses of 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 appear to occur by measures of baseline usage. Parents who used the system more at baseline saw smaller effects. Moreover, 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. To benchmark the amount of heterogeneity, 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. These results highlight the apparent complementarity between parent usage and teacher usage of the portal.

V Discussion and 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 families' adoption of a school communication technology that aims to scale school-to-family communication. Adoption is not universal; more than 40% of families have never logged into the system. Schools with higher login rates tend to serve higher income and higher performing students, which suggests that this technology may not close achievement gaps without active efforts to promote adoption and usage.

A simple intervention providing account information to parents increased families' adoption and usage by almost two logins per month. Interestingly, there were significant usage spillovers on families who did not receive the intervention. This increase in usage led to a modest increase in grades in both treated and spillover group students. Though these gains are small, the intervention has low marginal cost as well. The mailers cost $0.70 to print and send across two states. The phone calls cost $1.36 per student to manage and implement. Nonetheless, the effects on usage are far from sufficient to close the gaps between schools with high test scores and low test score or schools serving a majority of students who receive free or reduced priced lunch versus those that serve a majority of students who do not.

The results also emphasize the complementarity between parent usage and teacher usage of the portal. Both the usage and the GPA treatment effects are larger for schools in which teachers used the system more frequently. One might hope that the intervention could generate a demand shock for information sufficient enough to increase the supply information as proxied by teacher logins, but the study is underpowered to detect such effects.[6]

Overall, these results indicate both the promise and pitfalls of these technologies. Merely providing access to information online may not improve outcomes in low-income area schools and low-performing schools. Given the potential importance of this information and the barriers to online access, future research could examine the take up and efficacy of information technologies aimed at actively pushing information to parents at scale.

[6]There is no effect on teacher usage of the portal.

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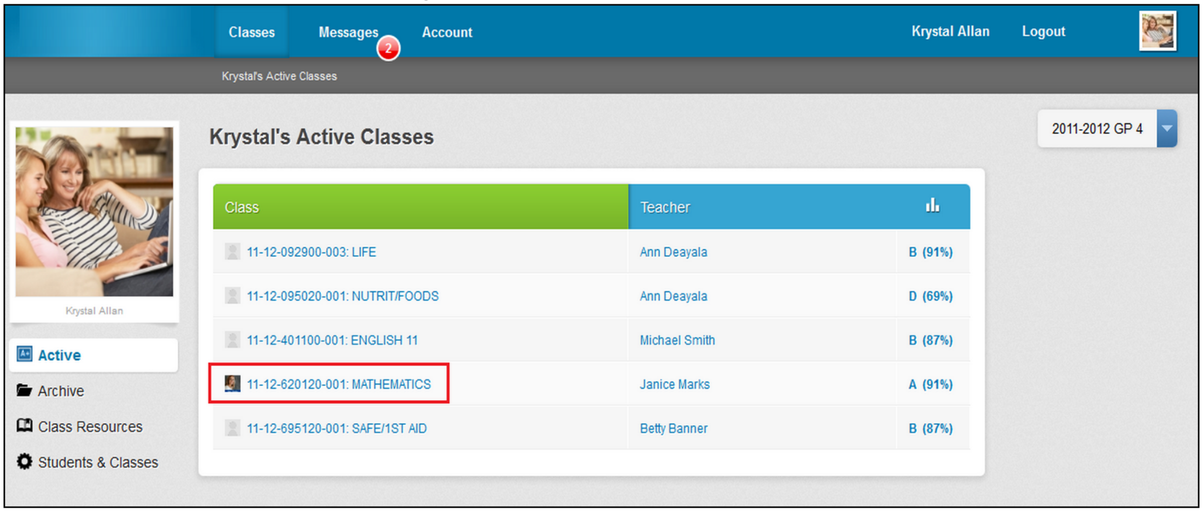
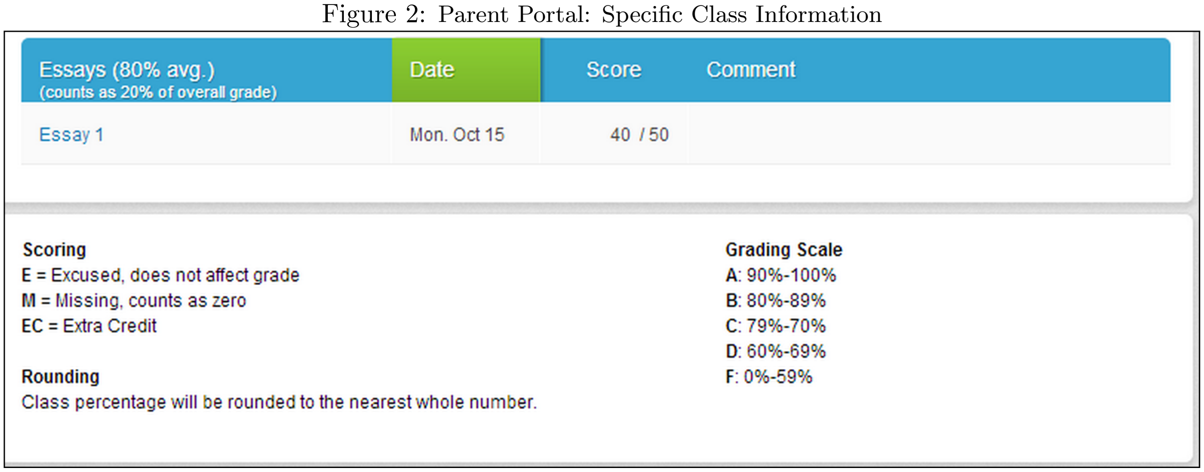
Figure 1: Parent Portal: Main Screen



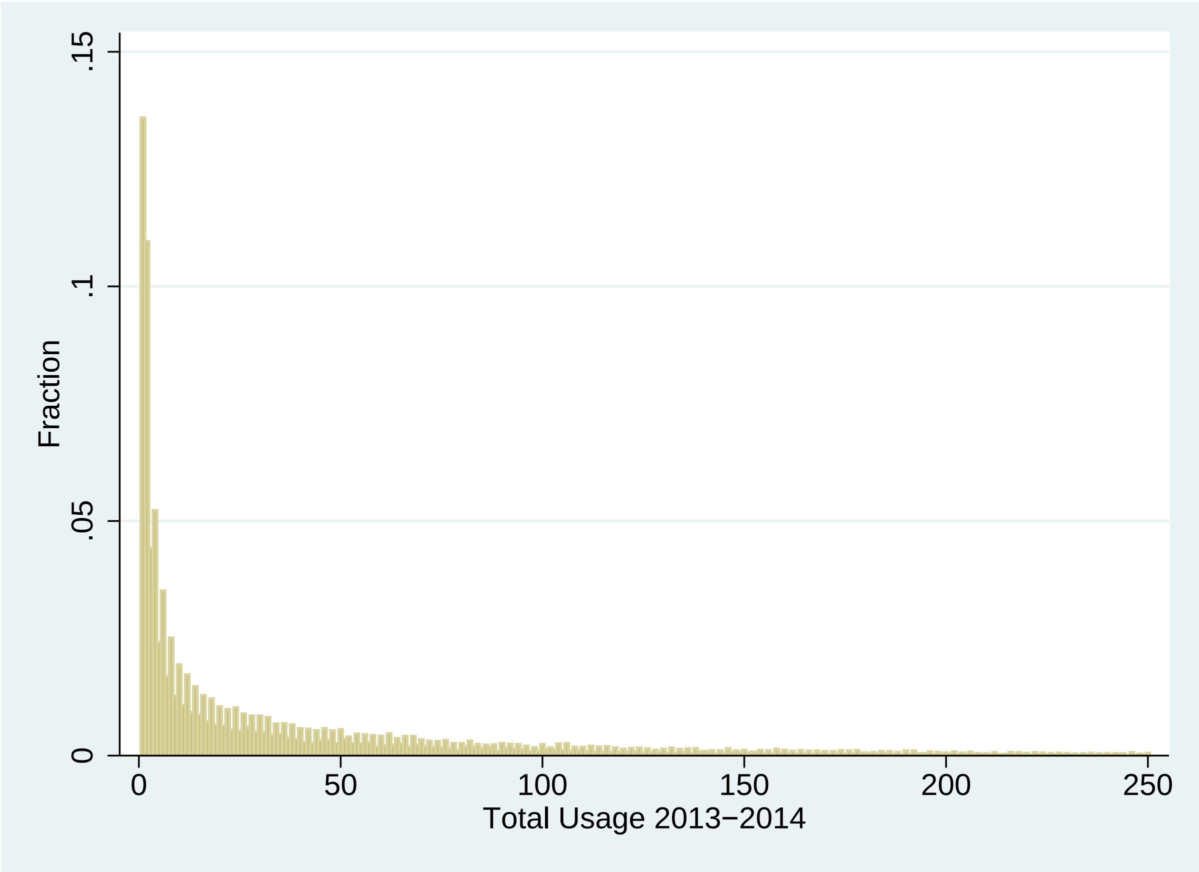
The figure shows an example of the type of academic information that can be found on parent portal. All information on this figure is fictional.

Figure 2: Parent Portal: Specific Class Information



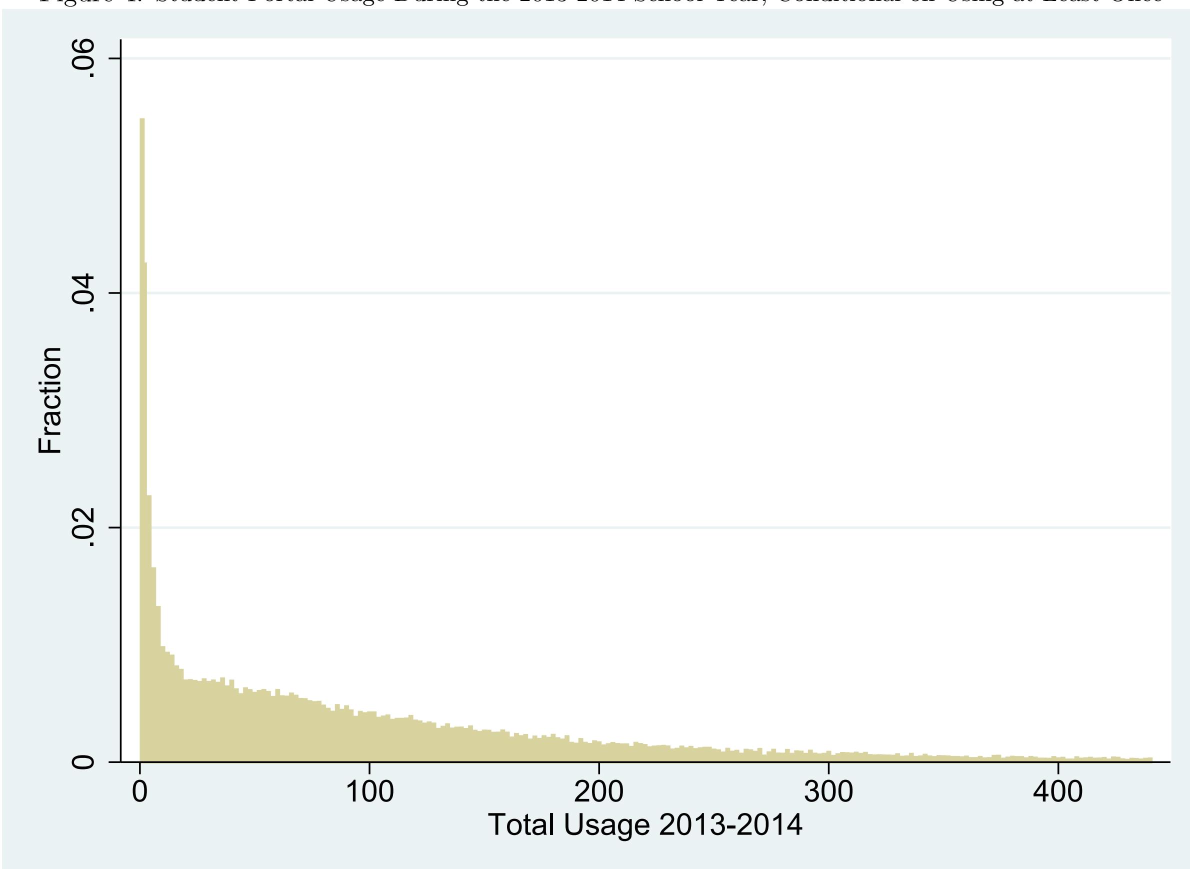
The figure shows an example of the type of academic information that can be found on parent portal once a parent clicks on a specific class. All information on this figure is fictional.

Figure 3: Parent Portal Usage During the 2013-2014 School Year, Conditional on Using at Least Once



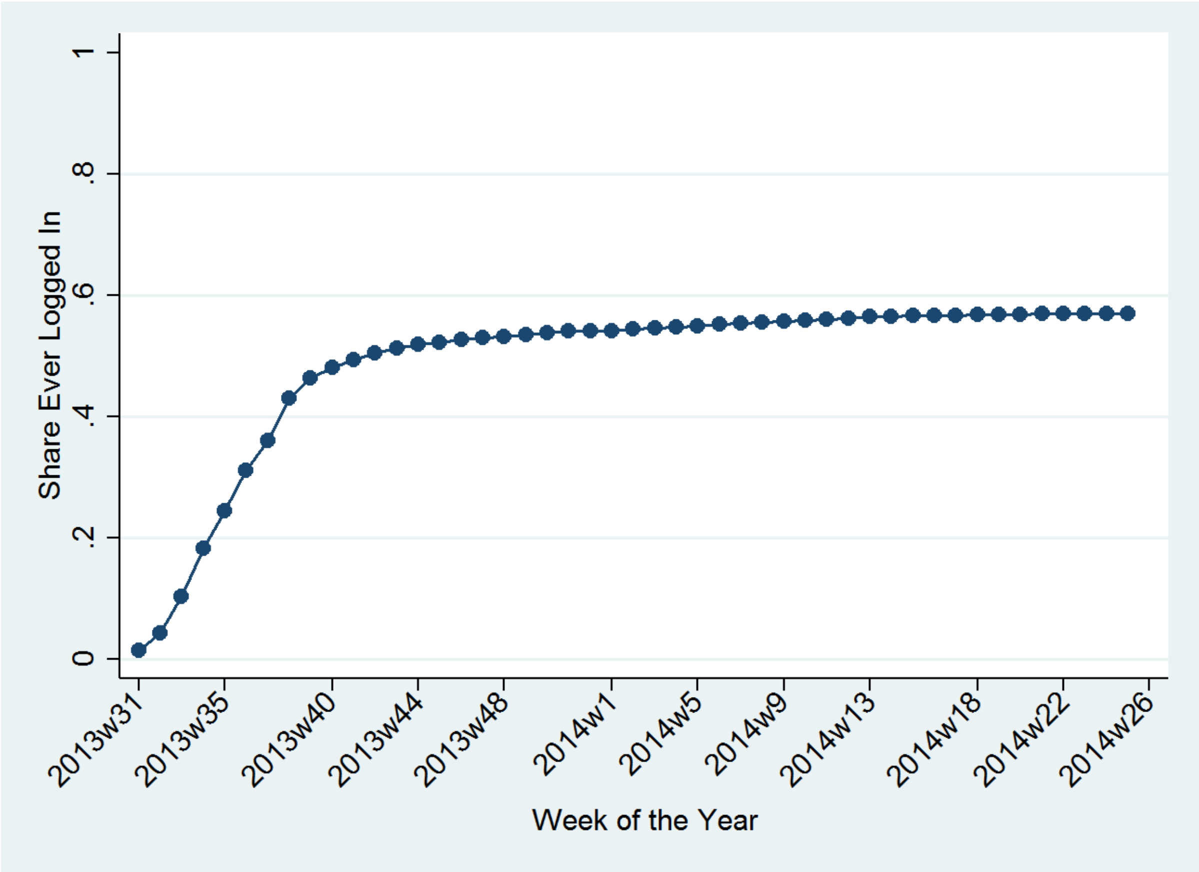
The figure shows the distribution of portal logins during the 2013-2014 school year conditional on logging in at least once. This figure is constructed using data from the Learning Management System and trims the top-most percentile from the data.

Figure 4: Student Portal Usage During the 2013-2014 School Year, Conditional on Using at Least Once



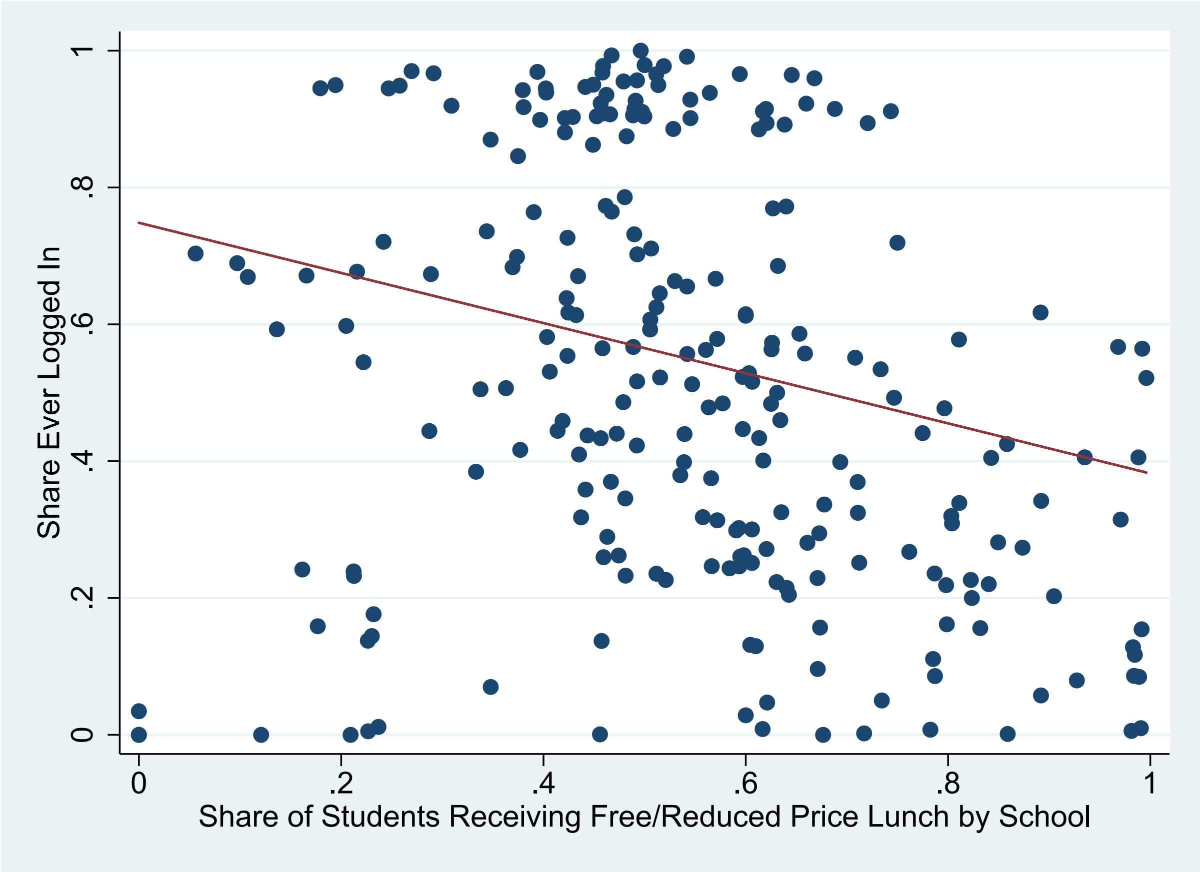
The figure shows the distribution of portal logins during the 2013-2014 school year conditional on logging in at least once. This figure is constructed using data from the Learning Management System and trims the top-most percentile from the data.

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



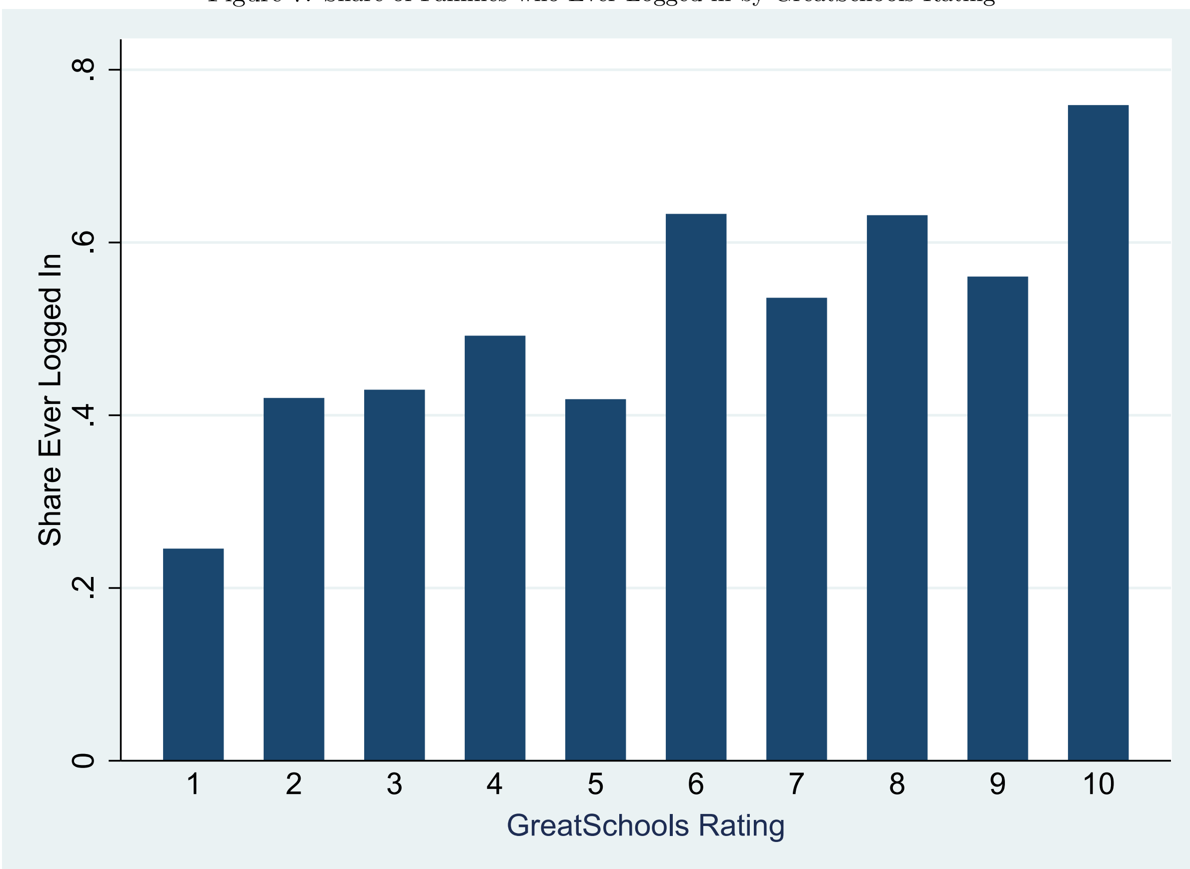
The figure shows the share of families who have ever logged into a portal during the 2012-2013 school year. This figure is constructed using data from the Learning Management System.

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



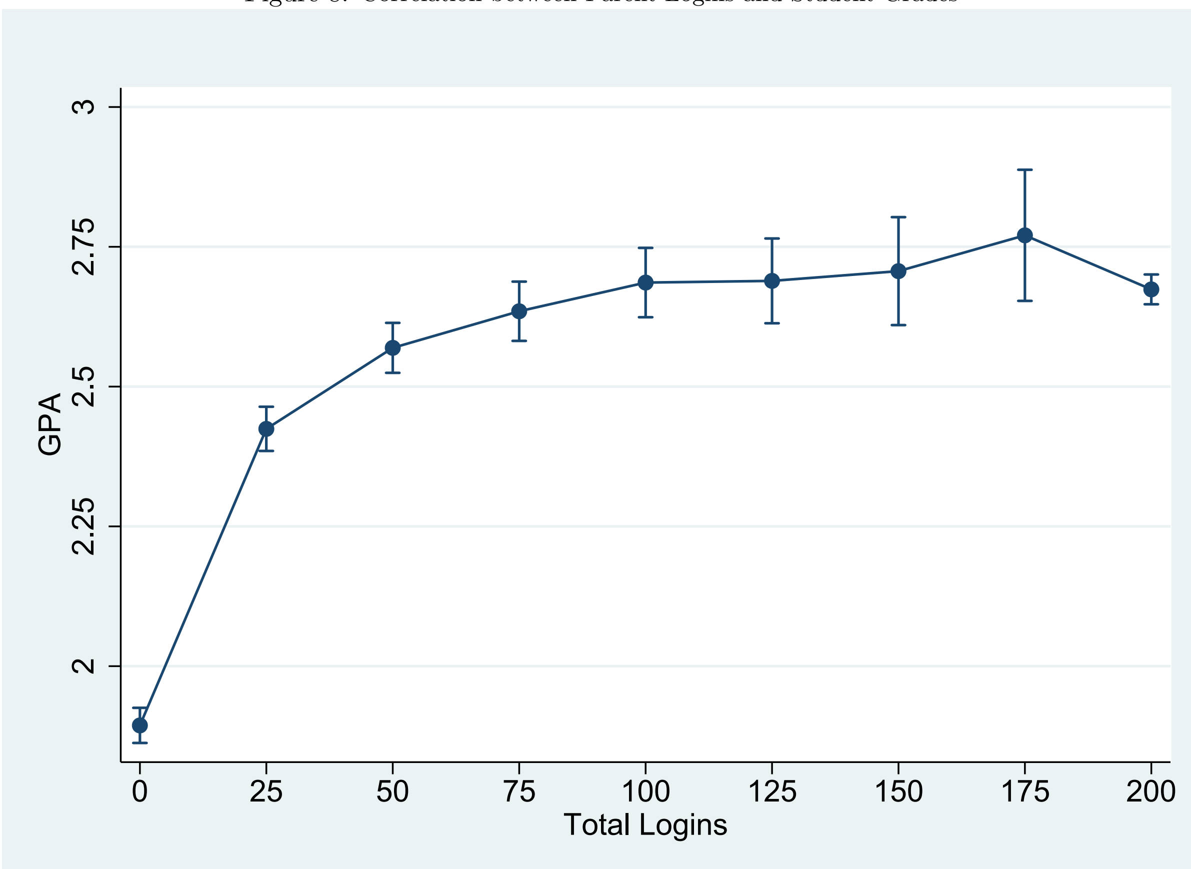
The figure shows the share of families who have ever logged into a portal plotted against the share of students who receive free/reduced price lunch in each school. This figure is constructed using data from the Learning Management System and NCES Common Core data.

Figure 7: Share of Families who Ever Logged in by GreatSchools Rating



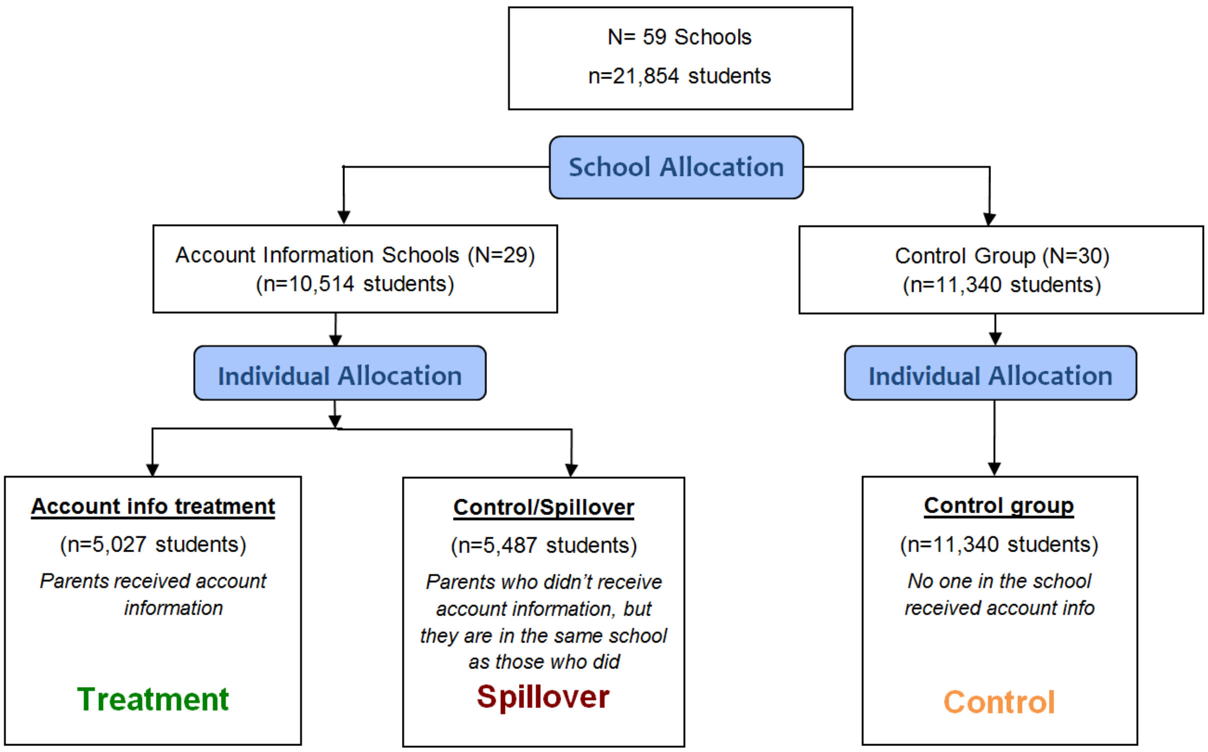
The figure shows the share of parents who have ever logged into a portal for each GreatSchools Rating of schools. This figure is constructed using data from the Learning Management System and GreatSchools ratings.

Figure 8: Correlation between Parent Logins and Student Grades



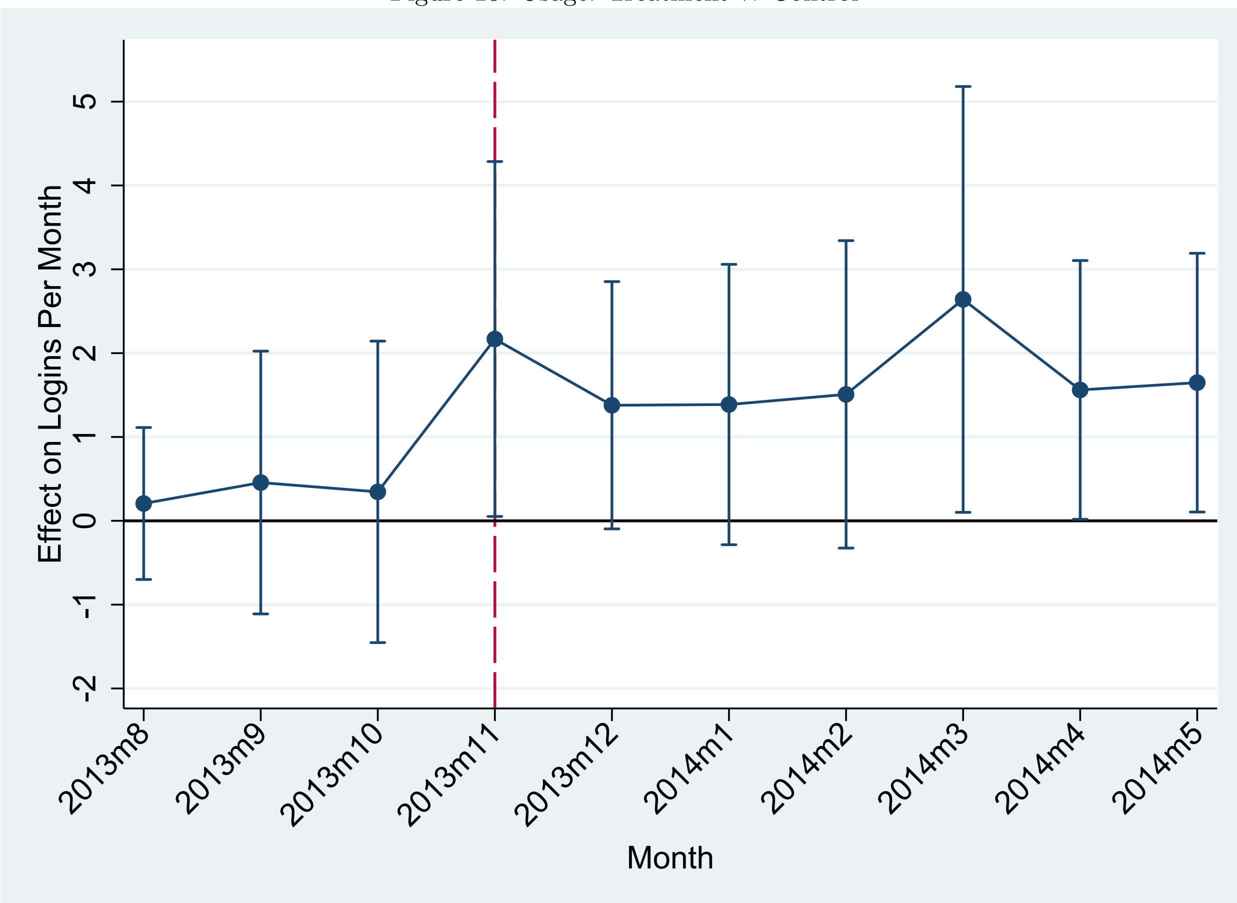
This figure shows the grade-point averages associated with different levels of portal usage relative. This figure is constructed using data from the Learning Management System.

Figure 9: Experimental Design



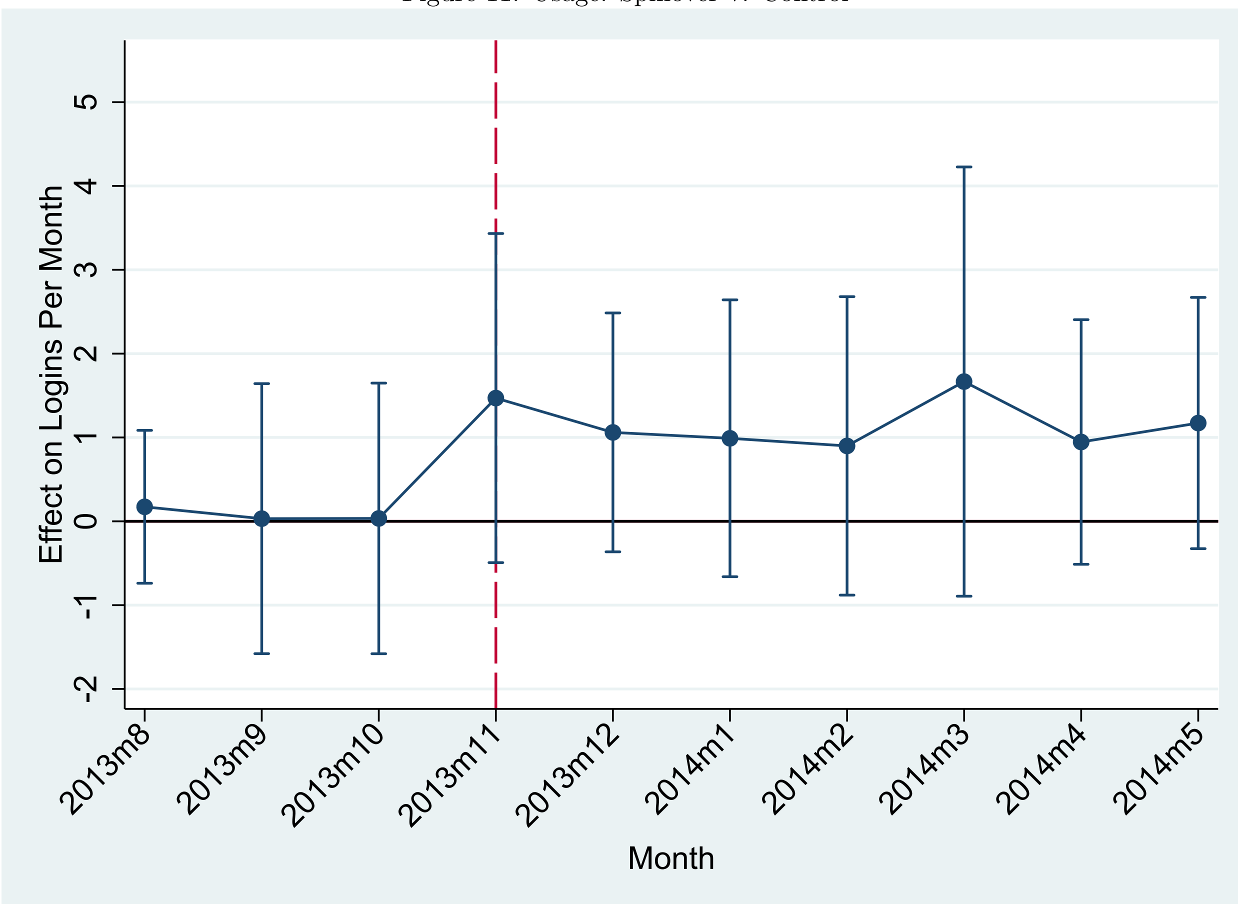
This figure shows the experimental design for the account-information intervention. Randomization occurs first at the school level and then at the student level.

Figure 10: Usage: Treatment v. Control



This figure shows the treatment effect on the number of times families logged in per month over the course of the school year. The vertical red line indicates when the treatment began. The effects are marginal effects at mean usage from the negative-binomial regression described in the text with usage for each month as the outcome. 95% confidence intervals shown. Data come from the LMS company.

Figure 11: Usage: Spillover v. Control



This figure shows the spillover effect on the number of times families logged in per month over the course of the school year. The vertical red line indicates when the treatment began. The effects are marginal effects at mean usage from the negative-binomial regression described in the text with usage for each month as the outcome. 95% confidence intervals shown. Data come from the LMS company.

Table 1: District Summary Statistics

Variable	Mean	Observations
Districts	N/A	15
Schools	N/A	264
Students	N/A	149,107
Female	49%	149,107
Share Hispanic	5.2%	244
Share Black	16.2%	244
Share White	77.5%	244
Share Free/Reduced Lunch	54.5%	244
Urban	21.5%	244
Suburb	20.7%	244
Town	15.1%	244
Rural	42.6%	244

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: 2013-2014

Variable	Mean	Observations
Parent Logins		
Share ever logged in	25%	149,107
Share who log in ≥1 per week	8%	6,956,448
Average Total logins	13	149,107
Student Logins		
Share ever logged in	49%	149,107
Share who log in ≥1 per week	22%	6,956,448
Average Total logins	48	149,107
Share any family ever logged in	57%	149,107

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	-0.24***	Hispanic	-0.04
	(0.09)		(0.18)
Middle School	0.26***	High School	-0.11**
	(0.04)		(0.04)
Share Free/Reduced Lunch	0.22	Suburban	0.03
	(0.17)		(0.04)
Urban	-0.05	GreatSchools Rating	0.020**
	(0.05)		(0.01)
Rural	0.01	Title I	-0.08*
	(0.04)		(0.05)
Student/Teacher	-0.01***	Logins/Teacher (thousands)	0.01***
	(0.00)		(0.00)
Observations	264 schools	145,139 students	
R-squared	0.69		

This table presents results from a student-weighted regression of the school-level share of families who have ever logged into the portal on school-level demographic and performance indicators. Student/teacher ratios are coded as missing if larger than 100. Teacher logins are coded as missing if larger than the 99th percentile of all logins. Log-in data are from the learning-management system on 264 schools representing 145,139 students linked to school-level data from the NCES Common Core Data. Missing values are imputed and indicators for missing data are included in the regression. 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.
<u>Treatment v. Control</u>						
GPA	2.43	2.48	-0.05	0.50	59	15,192
Fraction Missing	0.08	0.07	0.01	0.65	59	16,174
Parent Logins	0.60	0.74	-0.14	0.16	59	16,367
Student Logins	23.3	20.6	2.68	0.24	59	16,367
<u>Spillover v. Control</u>						
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	0.66	0.74	-0.08	0.43	59	16,827
Student Logins	22.7	20.6	2.71	0.21	59	16,827
<u>School Level</u>						
White	0.63	0.64	-0.01	0.64	58	N/A
Black	0.30	0.31	0.02	0.53	58	N/A
Hispanic	0.02	0.03	-0.01	0.64	58	N/A
Fraction FRL	0.60	0.61	-0.01	0.90	58	N/A
Rating	4.5	5.0	-0.49	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: Effects on Usage

Dependent variable	Total Logins	Total Logins	Ever Logged In	Ever Logged In
Treated school	12.07**	10.58**	0.07*	0.04**
	(6.12)	(4.89)	(0.04)	(0.02)
Spillover differential	-0.78	-1.01*	-0.04***	-0.03**
	(0.54)	(0.59)	(0.01)	(0.01)
Control mean	45.47		0.68	
Observations	21,854	21,854	21,854	21,854
Additional Controls	No	Yes	No	Yes

All data are at the student level and are constructed from the learning management company data. Total logins represents the total number of logins into the student or parent portal. Ever logged in is an indicator for whether there was any login to either the student or parent portal after the intervention. The *Spillover differential* variable show the difference in effect between the treatment group and the spillover group. The first two columns are marginal effects from a negative-binomial regression. Columns three and four are marginal effects from a linear-probability model. Additional controls described in the text. Marginal effects reported at baseline-mean usage. Standard errors clustered at the school level are shown in parentheses.

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

Table 6: Effects on Student GPA

Dependent variable	GPA	Z-Score
Treatment	0.11	0.10**
	(0.09)	(0.05)
Spillover differential	-0.06	-0.01
	(0.02)	(0.02)
Observations	19,218	19,218
Additional Controls	No	Yes

All data are at the student level and are constructed from the learning management company data. GPA standardized according to control-group means. The *Spillover differential* variable show the difference in effect between the treatment group and the spillover group. Additional controls variables described in the text. Standard errors clustered at the school level are shown in parentheses.

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

Appendix

Table A.1: Attrition

Dependent Variable	Has Final Grade
Treatschool	0.02
	(0.020)
Spillover	0.00
	(0.01)
Control mean	0.88
Observations	21,854

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

Table A.2: Subgroup Effects on Student GPA

Dependent variable	Grade Point Average							
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. Standard errors clustered at the school level are shown in parentheses.

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