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The inequity of opt-in educational resources and an intervention to increase equitable access

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Billions of dollars are invested in opt-in, educational resources to accelerate students' learning. Although advertised to support struggling, marginalized students, there is no guarantee these students will opt in. We report results from a school system's implementation of on-demand tutoring. The take up was low. At baseline, only 19% of students ever accessed the platform, and struggling students were far less likely to opt in than their more engaged and higher achieving peers. We conducted a randomized controlled trial (N=4,763) testing behaviorally-informed approaches to increase take-up. Communications to parents and students together increase the likelihood students access tutoring by 46%, which led to a four-percentage point decrease in course failures. Nonetheless, take-up remained low, showing concerns that opt-in resources can increase—instead of reduce—inequality are valid. Without targeted investments, opt-in educational resources are unlikely to reach many students who could benefit.

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Abstract

Billions of dollars are invested in opt-in, educational resources to accelerate students' learning. Although advertised to support struggling, marginalized students, there is no guarantee these students will opt in. We report results from a school system's implementation of on-demand tutoring. The take up was low. At baseline, only 19% of students ever accessed the platform, and struggling students were far less likely to opt in than their more engaged and higher achieving peers. We conducted a randomized controlled trial (N=4,763) testing behaviorally-informed approaches to increase take-up. Communications to parents and students together increase the likelihood students access tutoring by 46%, which led to a four-percentage point decrease in course failures. Nonetheless, take-up remained low, showing concerns that opt-in resources can increase—instead of reduce—inequality are valid. Without targeted investments, opt-in educational resources are unlikely to reach many students who could benefit.

Traditional schooling models are unlikely to combat pandemic-induced disruptions to learning that have widened already existing opportunity gaps (Dorn et al., 2021; Goldhaber et al., 2022). States, districts, and non-profit organizations are spending billions of dollars to provide programs and products that supplement students in-classroom experiences to accelerate learning recovery (Randazzo, 2022). Many of these resources are offered to students and their families free of cost. However, we have no guarantee that students will take advantage of educational resources, especially when they need to opt-in to use them. Research provides evidence that struggling and marginalized students will be less likely to take advantage of elective educational options, leading to the expansion, instead of reduction of educational disparities (see Hansen & Reich, 2015). In this paper, we demonstrate that providing access to educational resources will not mitigate learning gaps because the students who need support most are the least likely to use them. Through a randomized controlled trial, we show that targeted communications to parents and students together can substantially increase the likelihood students use a beneficial, opt-in educational resource—but not enough to address the learning disruptions that impacted a generation of students.

Tutoring is one of the most promising approaches for accelerating student learning and reducing educational disparities (Nickow et al., 2020). Over 100 randomized controlled trials have assessed the effectiveness of this approach—high-quality individualized instruction—with findings showing greater effectiveness than from reducing class sizes or teacher professional development programs (Dietrichson et al., 2017; Fryer, 2014). Individualized instruction can target students' learning needs and provide the support needed for students, even students far behind grade level, to succeed in school (Dietrichson et al., 2017; Neitzel et al., 2022).

As a result of the unusually strong evidence of the effectiveness of tutoring, many school districts, and even entire states, are offering students free access to on-demand tutoring programs (Goldstein, 2021). These programs can provide students with high-quality, well-trained tutors available for timely one-on-one educational support. Moreover, virtual, on-demand tutoring alleviates many of the logistical constraints schools perpetually face, because it does not rely on the local labor supply and students can access tutor support outside of school hours (e.g., Kraft & Falken, 2021; White et al., 2021).

Policymakers and educational leaders are investing in tutoring, at least in part, to help the students whose learning dropped during the pandemic (U.S. Office of the Press Secretary, 2022). Ample research shows that these students were more likely have lower prior achievement and come from lower income families and marginalized groups (Dorn et al., 2021; Goldhaber et al., 2022). For on-demand tutoring to benefit student learning, however, students need to sign on and request help from a tutor. We have little evidence about whether providing open access to tutoring leads these students to use the resource or how to enhance take-up among the students who need it most.

This manuscript reports results from the implementation of opt-in, on-demand tutoring in a school system in California serving low-income secondary school students. The implementation occurred during the Spring 2021 semester and included a large-scale randomized controlled trial (RCT) testing behaviorally-informed approaches to increase take-up of the program. The intervention delivered repeated rounds of personalized communications to students and/or parents encouraging student usage of the platform over the course of a semester (n=4,763). The RCT provides insights into both the potential of increasing take-up of opt-in educational resources and of the effectiveness of the program for improving the educational

outcomes of students who use it. Data from the study also shed light on the take-up rates for different groups of students in the absence of targeted encouragements.

Take-up of the program was low. Only 19% of students in the control group ever accessed the platform. Struggling students most in need of support, those who received a D or an F in at least one class in the prior semester, were far *less* likely to access the platform than students who passed all their classes (with a take-up rate of 12% vs. 23%, respectively). Our effort to increase take-up, tested by the RCT, was relatively successful. Sending personalized communications to both students and parents (the most effective treatment arm) increased use of the on-demand tutoring platform by 46%. These effects were even larger for struggling students, leading to a 122% increase in take-up. Nonetheless, this increase still only resulted in 26% of struggling students choosing to opt-in even once.

A potential explanation for not choosing to access the program would be if the program were not effective. However, although quantifying impacts on student achievement during the height of the pandemic is challenging, we find causal evidence that use benefits students. Being assigned to the most effective treatment arm translated into a four-percentage point (pp) increase in the likelihood students passed all their courses. When using the random variation in communications to students and parents as an instrument for taking up the resource, we find evidence that using on-demand tutoring positively impacted students' academic outcomes.

The concerns that opt-in, open access educational resources can enhance—instead of reduce—inequality are valid. Without targeted investments in increasing take-up, opt-in educational resources are unlikely to reach many students who could benefit from it. We find that a scalable intervention that engages students and their parents increases the likelihood struggling students use and benefit from on-demand tutoring. However, providing tutoring

during the school day and integrating tutoring with the schools instructional program so that the school determines which students participate in this high-return educational opportunity is far more likely to reach and benefit struggling students.

Study Details.

We conducted our study in partnership with Aspire Public Schools (Aspire), a public charter district in California. All Aspire middle and high school students (*n*=6,999) receive personal electronic devices and had free access to an on-demand tutoring platform for the Spring 2021 semester. We randomly assigned households to a control group or to one of three treatment arms involving communications to: (1) *Student Only*, (2) *Parent Only*, or (3) *Student+Parent*. We randomly selected one student from each household as the "focal" student for the intervention. Each communication to students and parents had a specific content focus drawing on prior successful behavioral interventions: reminders (e.g., Calzolari & Nardotto, 2017; Karlan et al., 2016), social norms (e.g., Allcott & Rogers, 2014), accountability (e.g., Gerber et al., 2008), and valuing of the subject (e.g., Robinson, Lee, et al., 2018).

We addressed two primary research questions:

1) To what extent do students take advantage of a free, on-demand tutoring resource provided by their school?
2) Can we increase take-up of on-demand tutoring with personalized communications to students and/or parents?

We also addressed two exploratory research questions:

3) Does take-up of on-demand tutoring lead to student learning gains?
4) What moderates the effect of personalized communications on take-up of on-demand tutoring and student learning gains?

Our paper contributes to several different literatures and has immediate implications for the role of open access technology, schools, and parents to support the provision of beneficial educational resources. First, we provide some of the first large-scale evidence on the extent to which students took advantage of free, open access educational resources provided by their school district during COVID-19. Second, we advance knowledge on how to effectively target and deploy behavioral interventions to encourage positive educational behaviors by students. Few studies to date examine K-12 students' take-up of optional educational learning resources and what might motivate usage. Moreover, we are among the first to present the comparative and marginal benefits of messaging parents *instead of* students and *in addition to* students on educational outcomes. Finally, to our knowledge, this is the first study to test the causal impact of on-demand tutoring on middle and high school student academic outcomes. At the college level, studies that increased students' usage of peer-tutoring resources failed to find statistically significant positive effects on student performance (Angrist et al., 2009; Paloyo et al., 2016; Pugatch & Wilson, 2018). Although we consider the achievement results exploratory due to the low quality of the academic data collected during the 2022-21 school year, we do see evidence that increasing students' usage of on-demand tutoring can reduce the likelihood students fail their academic courses.

Approach & Results

Sample and Procedures.

We included all Aspire middle and high school students who were enrolled during the Spring 2021 semester in our descriptive analyses (n=6,999). Seventy-five percent of Aspire students identified as Hispanic/Latinx, 9% as Black/African American 6% as Asian, and 4% as White/Caucasian. Over three-quarters of students qualified for free- or reduced-priced lunch

(FRPL), 13% of students were enrolled in special education services, and 56% of students lived in households who indicated their primary language was Spanish.

All middle and high school students enrolled during Fall 2020 were eligible for inclusion in the RCT sample (*n*=6,981; see Table 1 for exclusion criteria). Because our intervention involved communications to parents, we identified which students likely lived in the same household by shared parent contact information. In households with multiple students eligible for the intervention (*n*=2,980), we randomly selected one student as the focal student for the intervention. Ultimately, our RCT sample consisted of 4,763 students.

Table 1. Exclusion Details

Details of Participation	**N students**
Assigned to Treatment	4763
No Parent Contact Info	736
No Address	9
Sibling Assigned to Treatment	1384
Duplicate Household but Sibling Had no Parent Contact Info	89
Student Not in Initial (January 2021) Dataset	18

We then randomly assigned these students to a control group (*n*=1,188) or to one of three treatment arms, with randomization stratified by students' school, grade, and home language (Spanish or English): (1) *Student Only* (*n*=1,202), (2) *Parent Only* (*n*=1,192), or (3) *Student+Parent* (*n*=1,181). Students were balanced on baseline covariates across conditions (see Supplementary Table 1). Table 2 shows how the RCT sample differs from the overarching school sample.

Students assigned to the control group received no additional communications beyond what their school typically sends. Students assigned to the *Student Only* or *Student+Parent* treatment arm received an initial mailer sent to their home address which included a letter that introduced the on-demand tutoring platform and provided information on how to access the

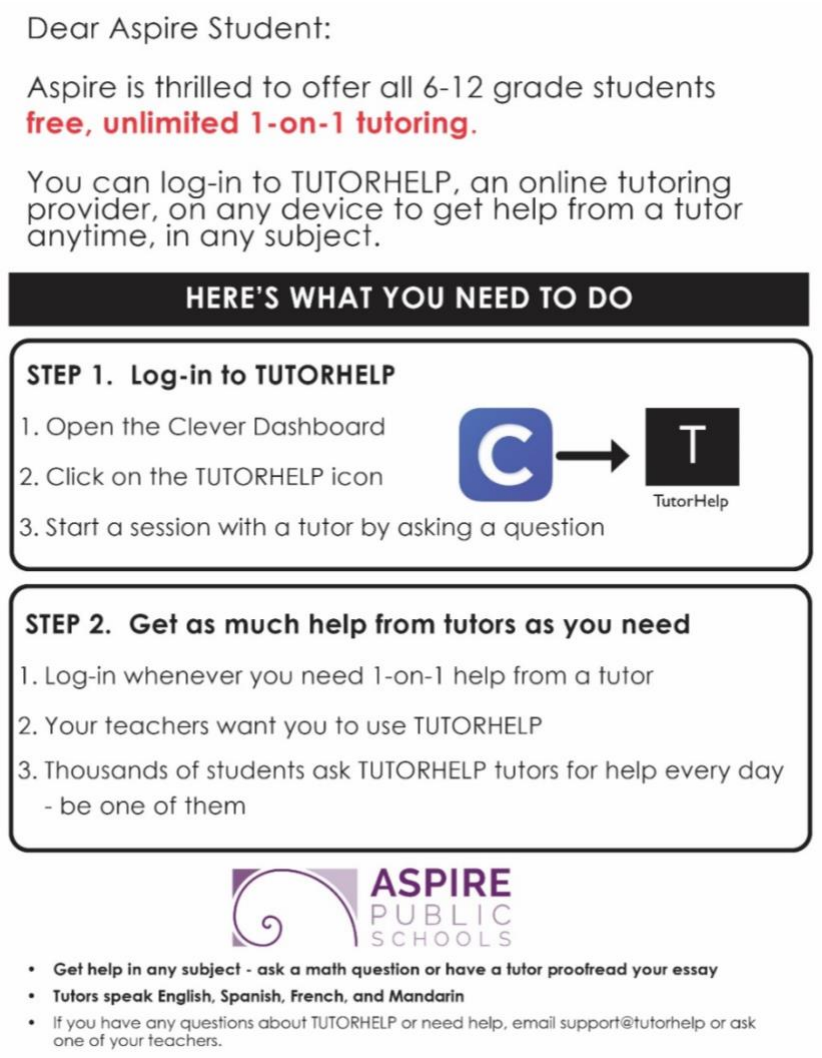
Table 2. Sample Details by Student Background Characteristics

	All Students	**Students excluded from RCT sample**	**Students in RCT sample**	**%point Diff (excluded vs. sample)**	**p-value (excluded vs. sample)**	**Spillover students in Treated Households - Siblings Excluded from RCT**
Female	0.487	0.508	0.482	-0.022	0.321	0.494
FRPL	0.766	0.789	0.756	-0.018	0.352	0.788
Special Education indicator	0.126	0.122	0.125	-0.006	0.681	0.132
Spanish-Speaking HH	0.560	0.554	0.563	0.000	0.328	0.551
Asian	0.064	0.049	0.059	-0.006	0.690	0.089
Black	0.088	0.096	0.097	0.008	0.576	0.055
Hispanic	0.754	0.708	0.756	0.036	0.006	0.772
White	0.044	0.021	0.047	0.020	0.015	0.045
Other Race	0.029	0.025	0.030	0.001	0.950	0.028
Passing All Courses (Fall 20)	0.757	0.735	0.761	0.042	0.026	0.758
No Fs in Courses (Fall 20)	0.570	0.512	0.582	0.089	0.000	0.559
Passing Math Courses (Fall 20)	0.888	0.858	0.892	0.048	0.003	0.893
No Fs in Math Courses (Fall 20)	0.742	0.682	0.751	0.080	0.001	0.742
N	6999	749	4763			1487

Notes. Passing All Courses means students earned a C- or better in all courses.

Figure 1. Initial Mailer for Students and Parents

A. Students



B. Parents

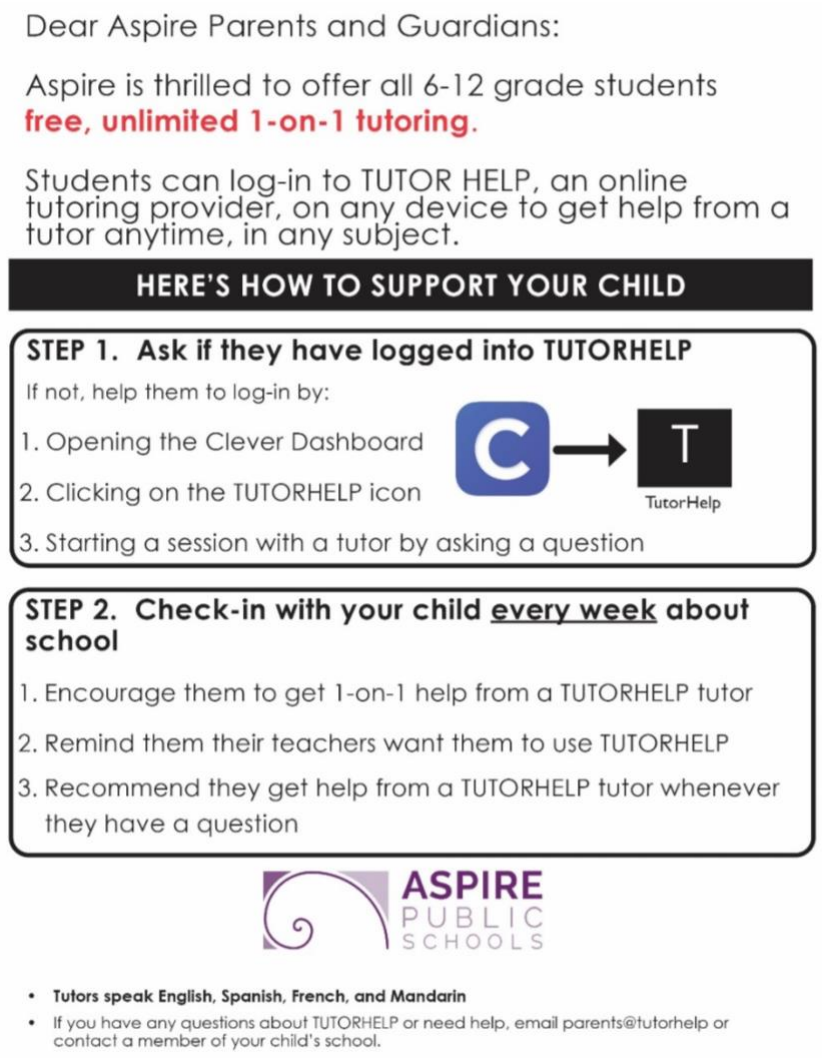
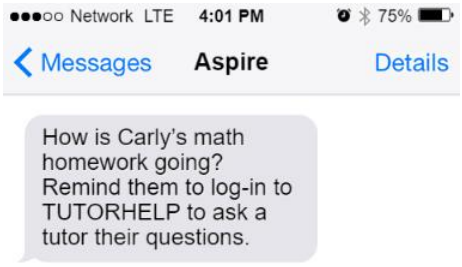


Figure 2. Sample Emails to Students and Text Messages to Parents by Message Type

A. Reminder



How is your math homework going?

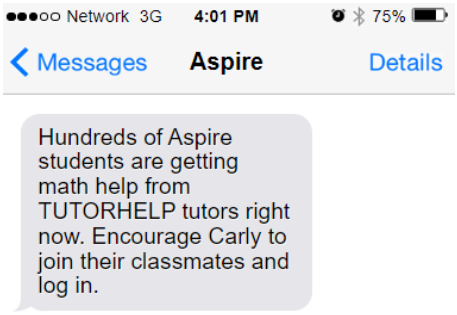
From: TUTORHELP Tutoring

to me

Hey Carly – how's your math homework going today?

Log-in to TUTORHELP right now to ask a tutor a question you are stuck on!

B. Social Norms



Join your classmates on TUTORHELP

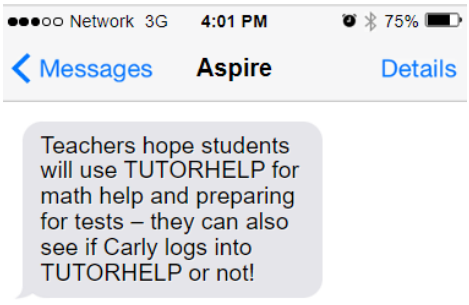
From: TUTORHELP Tutoring

to me

Hey Carly – Hundreds of Aspire students are getting math help from TUTORHELP tutors right now.

Be one of them! Log-in to TUTORHELP right now to ask a tutor a question you are stuck on!

C. Accountability



Teachers want you to use TUTORHELP

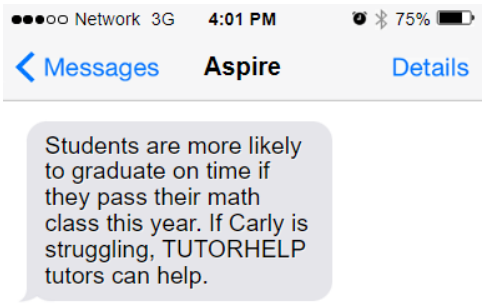
From: TUTORHELP Tutoring

to me

Hey Carly – your math teachers hope you will use TUTORHELP for getting homework help and preparing for tests. Your teachers can also check to see if you are logging in or not.

Log-in to TUTORHELP right now to ask a tutor a question you are stuck on!

D. Valuing of Subject



Increase the odds you graduate on-time

From: TUTORHELP Tutoring

to me

Hey Carly – did you know that students who pass their math class this year are more likely to graduate on time?

If you are struggling or if you want to get ahead – log-in to TUTORHELP right now to ask a question you are stuck on!

platform and tips on how to engage (see Figure 1A). The letter was accompanied by post-it notes that we branded with the on-demand tutoring platform's logo and "Unlimited 1-on-1 Tutoring." They also received 16 personalized emails to their school-provided email address over the course of the semester. For those students assigned to the *Parent Only* or *Student+Parent* treatment arms, one of their parents received a similar initial mailer (see Figure 1B) and branded post-it notes. Parents, too, received 16 personalized text messages. If the initial text message was undeliverable, we sent the rest of the communications to parents via email. Ultimately, 92.25% of parents in the *Parent Only* and *Student+Parent* treatment arms received the intervention via text messages and the remaining 7.75% received emails.

After the first introductory email or text message, each communication students or parents received encouraged students to access the on-demand tutoring platform. Students could receive help from tutors in any core subject, however the communications focused on encouraging students to use the resource specifically for math-related coursework. Each communication was written to align with one of four types of behavioral strategies: reminders, social norms, accountability, and valuing of the subject (see Figure 2 for example messages). For communications 2-6, we randomly assigned students within each treatment arm to receive one of the four messages (re-randomizing for each subsequent communication). Thus, we were able to test whether specific behavioral strategies drove more engagement in the 48 hours after receipt. For communications 7-16, each communication students and parents in the treatment conditions received targeted one behavioral strategy. More details on the procedure can be found in the additional Methods section at the end of the manuscript.

Outcome Measures.

Our primary outcome was whether students take-up the on-demand tutoring platform. We defined take-up as logging on and engaging in at least one session with a tutor. As additional measures of engagement, we also explored how many sessions students engaged in on the platform and the number of messages they exchanged with tutors.

We used student course performance data available during the 2020-21 school year to assess academic outcomes. This aligned with the goal of the implementation: Aspire district leaders observed a sharp rise in the number of students earning non-passing grades in Fall 2020. This observation was a primary reason why the leadership team contracted with an on-demand tutoring provider that could serve all middle and high school students—they wanted to reduce the likelihood students were receiving Ds and Fs in core courses.

The COVID-19 pandemic caused many U.S. districts—including Aspire—to forego standardized testing and alter their standard grading schemes (U.S. Department of Education, 2020), making it hard to assess student achievement. During the 2020-21 school year, Aspire did not consistently administer standardized tests, allowed students to take courses for "Credit" or "No Credit" (i.e., Pass/No Pass) instead of letter grades, and changed the criteria for receiving course credit. These decisions were largely the result of federal or statewide legislation. In California, the Governor signed Assembly Bill 104 (Gonzalez) on July 1, 2021 which provided for a limited process to request that high school grades earned during the 2020-21 school year be changed from a letter grade to Pass or No Pass. Prior to the pandemic, Ds were not considered a passing grade in Aspire. These graduation requirements aligned with what is required by University of California/California State University (UC/CSU) admissions (University of California Admissions). However, for the 2020-21 and 2021-22 school years, Aspire allowed

students who earned a D in a course to earn credit for taking the course (although the state college admission requirements did not change).

Given the specific context, we focused on three academic outcome measures: (1) an indicator for whether a student passed all their Spring 2021 core courses with a C- or higher (passed) which aligned with the district's pre-pandemic standards and UC/CSU graduation requirements, (2) whether a student passed all their Spring 2021 core courses with no failures (no Fs) to reflect the district's relaxed standards during the pandemic, and (3) Spring 2021 semester GPA. Because the intervention itself focused on encouraging students to use the resource specifically for math, we also measured whether a student passed their math courses, did not receive an F in a math course, and their math GPA for the Spring 2021 semester. More details on the data and analytic strategy can be found in the additional Methods section at the end of the manuscript.

To what extent do students take advantage of a free, on-demand tutoring resource provided by their school?

In the control group, 18.69% of students ever accessed the platform and engaged in a tutoring session. On average, students in the control group participated in 0.80-sessions (*SD* = 3.76) and exchanged 27.29 messages with a tutor (*SD* = 146.33). We also found that there was substantial variation between grade levels and schools, with take-up rates ranging from 11.62% in 7th grade to 26.53% in 9th grade (see Supplementary Table S1 and Figure S1 for more details). Among students who ever accessed the platform, they, on average, attended 4.3 sessions (*SD* = 7.79) and exchanged 146.05 messages with a tutor (*SD* = 312.38).

Take-up of on-demand tutoring differed by students' prior course performance. Among students who passed all their Fall 2020 courses, 22.69% took up the resource, compared to only 11.64% of students who received a D or F in the prior semester, *SE* = 0.023, *t* = 4.84, *95% CI*

[0.066, 0.155], $p < .001$. Take-up on-demand tutoring did not meaningfully differ by students' special education status, eligibility for FRPL, race, or primary home language in the control group (see Supplementary Table S3). However, 23.15% of female students used on-demand tutoring compared to only 14.8% of male students, *SE* = 0.023, *t* = 3.70, *95% Confidence Interval (CI)* [0.039, 0.128], $p < .001$.

Can we increase take-up of on-demand tutoring with personalized communications to students and/or parents?

Figure 3 and Table 3 (columns 1-4) shows how each of the treatment arms impacted student take-up of on-demand tutoring compared to the control group. For precision, our preferred model includes student covariates, an indicator for student prior course performance, and strata fixed effects. Students assigned to the *Student Only* treatment arm did not increase their usage of the resource relative to the control group. Students assigned to the *Parent Only* treatment arm were 5.66-pp more likely to use on-demand tutoring than the control group. The *Student+Parent* treatment arm was most effective, leading to a 8.57-pp increase in the likelihood students took advantage of the on-demand tutoring resource compared to the control group. Supplementary Table S4 shows how each treatment arm performed compared to one another. The difference in take-up between the *Student Only* arm compared to the *Parent Only* and *Student+Parent* arms were statistically significant at the 0.1% level. Students assigned to the *Student+Parent* arm were 2.91-pp more likely to use on-demand tutoring than those assigned to the *Parent Only* arm, *SE* = 0.015, *t* = 1.89, *95% CI* [-0.001, 0.059], *p* = .059.

In columns 5-8 and 9-12 of Table 8, we show the impact of each condition on the number of on-demand tutoring sessions students engaged in and the number of messages they exchanged with virtual tutors, respectively. On average, students assigned to the *Student+Parent* treatment

Table 3. Impact of Experimental Condition on Engagement with Tutoring Platform

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Take-up				**Number of sessions**				**Number of messages exchanged**			
Student	0.011	0.011	0.009	0.008	-0.122	-0.118	-0.124	-0.129	4.277	4.513	4.493	4.070
	(0.016)	(0.014)	(0.014)	(0.014)	(0.134)	(0.112)	(0.112)	(0.112)	(8.007)	(7.881)	(7.758)	(7.706)
Parent	0.058***	0.056***	0.056***	0.057***	0.084	0.065	0.075	0.076	4.915	4.343	4.660	4.761
	(0.017)	(0.015)	(0.015)	(0.015)	(0.152)	(0.120)	(0.119)	(0.119)	(5.987)	(5.433)	(5.476)	(5.476)
Student+Parent	0.086***	0.086***	0.085***	0.086***	0.591**	0.593**	0.589**	0.593**	37.260**	37.489**	37.576**	37.867**
	(0.017)	(0.015)	(0.015)	(0.015)	(0.213)	(0.185)	(0.188)	(0.188)	(12.543)	(12.022)	(12.458)	(12.502)
Constant	0.187***	0.187***	0.121***	0.080**	0.803***	0.806***	0.350*	0.136	27.291***	27.318***	10.573	-8.991
	(0.011)	(0.010)	(0.028)	(0.029)	(0.109)	(0.081)	(0.158)	(0.182)	(4.245)	(3.785)	(10.190)	(13.253)
Student Controls	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Prior achievement	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Strata FE	No	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	No	No
Adjusted R-squared	0.006	0.185	0.191	0.197	0.003	0.240	0.241	0.242	0.003	0.071	0.071	0.073
Observations	4763	4763	4763	4763	4763	4763	4763	4763	4763	4763	4763	4763

Notes. The Prior Course Performance indicator includes a category for missing. Student Controls include dummy variables for Female Free/Reduced Lunch SPED Race/Ethnicity categories and a missing indicator for Race/Ethnicity.

Standard errors in parentheses

+ p<0.1, * p<0.5, ** p<0.01, *** p<0.001

Figure 3. Take-up by Condition and Prior Performance

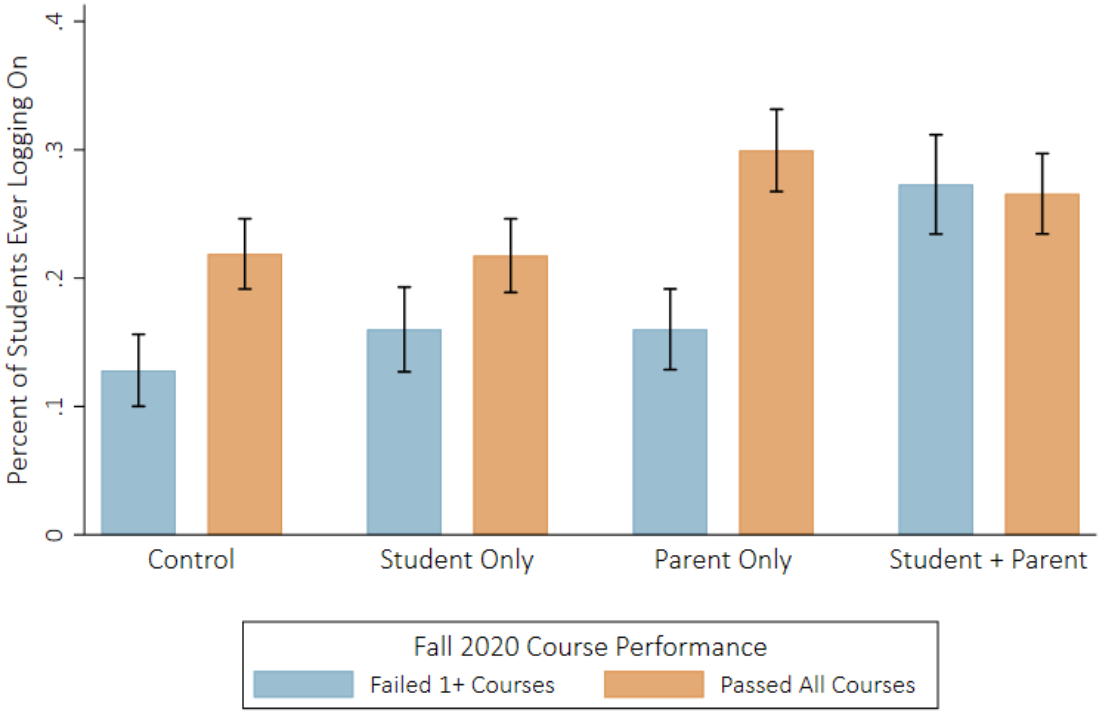
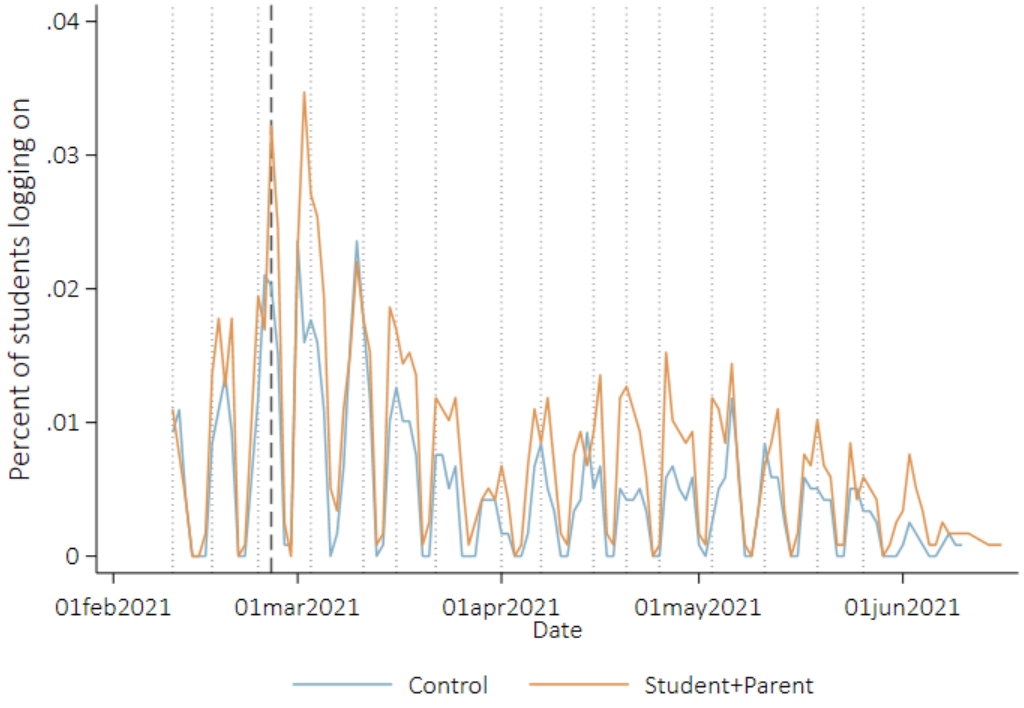


Figure 4. Usage of Tutoring by Condition Over Time: Student+Parent vs. Control



Notes: Each dotted line represents the date email and text message communications to students and parents were sent. The dashed line represents the date the mailers started to hit households.

arm attended 1.4 sessions (*SD* = 6.3) and exchanged 64.55 messages with tutors (*SD* = 405.63), which was more than students in each of the other conditions.

Figure 4 illustrates how usage of the on-demand tutoring resource varied over time for students assigned to the control group (blue line) and those assigned to the *Student+Parent* treatment arm (orange line). In general, students were less likely to sign on to receive help from a tutor as the semester progressed. Visually, the personalized communications to students and their parents resulted in a small increase in students accessing tutoring after each communication.

Does take-up of on-demand tutoring lead to student learning gains?

We present three analyses exploring how on-demand tutoring may associate with student learning. First, controlling for underlying student characteristics and prior performance, we found that students who ever had a tutoring session were 10.28-pp more likely to pass all their core courses than their peers who never accessed the on-demand tutoring platform, *SE* = 0.012, *t* = 8.75, *95% CI* [0.08, 0.126], $p < .001$. They also earned a grade point average (GPA) that was 0.273-points higher in their core courses, *SE* = 0.03, *t* = 9.15, *95% CI* [0.215, 0.332], $p < .001$. However, these correlational analyses do not account for unobservable student characteristics, like motivation.

Second, we estimated the impact of our RCT on student course performance. We use our preferred model to assess the impact of treatment assignment on students' likelihood of passing all courses, receiving no Fs, and on semester GPA in their core courses (including math; Table 4; columns 1-3) and in their math courses, specifically (Table 4; columns 4-6). Students assigned to the *Student+Parent* treatment were 4.02-pp more likely to pass all their Spring 2021 courses. At the same time, students assigned to the *Parent Only* and *Student+Parent* treatments were equally likely to earn an F in a course during the Spring 2021 semester. Unexpectedly, students assigned

Table 4. Impact of Experimental Condition on Spring 2021 Course Performance

	All Core Courses			Math		
	(1)	(2)	(3)	(4)	(5)	(6)
	Passing	**No Fs**	**GPA**	**Passing**	**No Fs**	**GPA**
Student	-0.003	-0.034*	-0.063	-0.022	-0.017	-0.056
	(0.015)	(0.014)	(0.041)	(0.018)	(0.014)	(0.047)
Parent	0.007	-0.011	0.012	0.006	-0.003	0.054
	(0.015)	(0.015)	(0.041)	(0.018)	(0.014)	(0.048)
Student+Parent	0.040*	0.004	0.028	0.016	-0.000	0.087+
	(0.016)	(0.015)	(0.042)	(0.018)	(0.014)	(0.047)
Constant	0.256***	0.484***	1.851***	0.460***	0.771***	1.613***
	(0.027)	(0.027)	(0.071)	(0.030)	(0.025)	(0.084)
Student Controls	Yes	Yes	Yes	Yes	Yes	Yes
Prior achievement	Yes	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.465	0.364	0.509	0.396	0.212	0.508
Observations	4542	4542	3616	2849	2849	3240

Notes. Our preferred model controls for student-level characteristics prior course performance has a fixed effect for strata and uses cluster robust standard errors. Student Controls include dummy variables for gender, FRPL, special education status, Race/Ethnicity categories, and a missing indicator for Race/Ethnicity.

Standard errors in parentheses

+ p<0.1, * p<0.5, ** p<0.01, *** p<0.001

to the *Student Only* condition appear to be 3.42-pp *more* likely to earn an F in at least one course during the Spring 2021 semester. Compared to the control group, we found no evidence the treatment affected whether students earned higher GPAs and no consistent impact on math course performance during the Spring 2021 semester. Supplementary Table S4 shows the difference between treatment arms. Compared to students assigned to the *Student Only* and *Parent Only* arms, students assigned to the *Student+Parent* arm were 4.36-pp and 3.3-pp more likely to pass their Spring 2021 courses, respectively.

Third, we estimated the causal impact of using on-demand tutoring on student academic performance among those who took-up the program. To do so, we take an instrumental variable approach using the exogenous assignment to one of the treatment arms as an instrument for taking up the resource. Our findings in Table 5 show that using on-demand tutoring had a positive effect on students' Spring 2021 academic outcomes, including the likelihood students pass all their courses (42.35-pp), the likelihood students receive no Fs (18.79-pp), students' overall GPA (0.77-points), and students' math GPA (1.32-points). Given the relatively weak instrument, these estimates are imprecise and vary in whether each confidence interval overlaps with zero. However, these results suggest that students can benefit academically if they log-on and request help from on-demand tutors.

What moderates the effect of personalized communications on take-up of on-demand tutoring and student learning gains?

Finally, we assessed heterogeneity in the treatment effect based on message type and students' underlying characteristics. We found no evidence that the content of the personalized messages (i.e., reminder, social norms, accountability, valuing) had any impact on whether students logged on to use the on-demand tutoring resource in the subsequent 48 hours (see Table

Table 5. Instrumental Variable approach to estimating impact on academic outcomes

Panel A. 2SLS	All courses			Math
	Passing	No Fs	GPA	GPA
Ever logged on	0.423**	0.188	0.773+	1.37*
	(0.161)	(0.148)	(0.450)	(0.490)
Student controls	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes
Panel B. First Stage	Take-up			
Student	0.011	0.011	0.004	0.000
	(0.015)	(0.015)	(0.017)	(0.018)
Parent	0.060***	0.060***	0.054**	0.054**
	(0.015)	(0.015)	(0.017)	(0.018)
Student+Parent	0.087***	0.087***	0.078***	0.087***
	(0.016)	(0.016)	(0.018)	(0.019)
F statistics	13.25	13.25	8.96	9.69
chi2	41.16	41.16	27.93	30.27
Obs	4,541	4,541	3,613	3,239

Notes. All models control for student-level characteristics, prior course performance, includes a fixed effect for strata, and robust standard errors.

Standard errors in parentheses

+ p<0.1, * p<0.5, ** p<0.01, *** p<0.001

Table 6. Impact of different communications on engagement in subsequent 48 hours

	Logged on within 48 hours			
	All	Student	Parent	Student+Parent
Reminder (Reference)	0.033***	0.026***	0.035***	0.040***
	(0.003)	(0.004)	(0.005)	(0.005)
Social Norms	0.001	0.002	0.000	0.001
	(0.004)	(0.007)	(0.007)	(0.009)
Accountability	-0.005	-0.005	-0.013+	0.004
	(0.004)	(0.007)	(0.008)	(0.008)
Valuing	-0.004	-0.002	-0.006	-0.003
	(0.004)	(0.007)	(0.007)	(0.008)
Treat FE	Yes	No	No	No
R^2	0.378	0.349	0.349	0.416
Observations	17650	6010	5850	5790

Notes. The reference category is Reminder (i.e., impact of the reminder messages) and all of the other estimates are compared to the reminder messages. The first column includes students in all treatment arms and includes a fixed effect for treatment assignment, where the next three columns show the estimates for message type within each treatment arm.

Standard errors in parentheses

+ p<0.1, * p<0.5, ** p<0.01, *** p<0.001

6). The variation in these messages, however, does ease any worry that the results of this study depend on the specific wording we used in the messages.

Supplementary Tables S5A-E show how the treatment effect interacted with student gender, eligibility for FRPL, Fall 2020 course performance, primary home language, and special education status. In general, we saw that the impact of personalized communications tended to be largely consistent across student subgroups: students assigned to the *Student+Parent* treatment were the most likely to use the on-demand tutoring and tended to perform better academically. However, there is suggestive evidence that the intervention did have oversized impacts on students who were struggling academically or who may face additional stressors (e.g., coming from families who have lower incomes). As shown in Table 7, among students assigned to the *Student+Parent* treatment, those students who struggled in the Fall semester were 14.21-pp more likely to use the resource. Comparatively, students who passed all their Fall 2020 courses experience only a 4.22-pp increase. Encouraging usage among students and parents effectively eliminated the gap in take-up between students who struggled in the Fall and those who passed all their courses. Table 8 breaks down take-up by whether students were eligible for FRPL. Among students assigned to the *Student+Parent* treatment, we found that those eligible for FRPL were 5.69-pp more likely to pass all their Spring courses whereas there was no difference in passage rates for students from higher-income backgrounds.

Discussion

In this paper, we provide evidence that mere access to quality educational resources may not reduce, and may in fact increase, inequalities. We found that the vast majority of students do not take-up an opt-in educational resource, even when it can promote learning, and that struggling students are the least motivated to proactively access and benefit from the additional

Table 7. Outcomes by Prior Course Performance

	Passed all Fall 2020 Courses				**At Least 1 D or F in Fall 2020**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ever logged on	Number of sessions	Passing	No Fs	Ever logged on	Number of sessions	Passing	No Fs
Student	-0.005	0.144	0.018	-0.008	0.033	-0.037	-0.027	-0.062*
	(0.020)	(0.142)	(0.020)	(0.013)	(0.022)	(0.113)	(0.024)	(0.029)
Parent	0.075***	0.239+	0.019	-0.009	0.033	-0.013	0.006	-0.008
	(0.021)	(0.134)	(0.020)	(0.013)	(0.021)	(0.109)	(0.025)	(0.029)
Student+Parent	0.042*	0.587*	0.038+	-0.008	0.142***	0.572**	0.043+	0.015
	(0.021)	(0.249)	(0.020)	(0.013)	(0.024)	(0.215)	(0.025)	(0.030)
Constant	0.159***	0.136	0.913***	0.982***	0.014	-0.023	0.107*	0.424***
	(0.037)	(0.204)	(0.030)	(0.020)	(0.043)	(0.185)	(0.053)	(0.062)
Student Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.221	0.069	0.141	0.040	0.111	0.070	0.115	0.197
Observations	2662	2662	2649	2649	1914	1914	1893	1893

Notes. Our preferred model controls for student-level characteristics has a fixed effect for strata and uses cluster robust standard errors. Student Controls include dummy variables for gender, FRPL, special education status, Race/Ethnicity categories, and a missing indicator for Race/Ethnicity.

Standard errors in parentheses

+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

Table 8. Outcomes by Free & Reduced Priced Lunch Status

	Not eligible for FRPL				Eligible for FRPL			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ever logged on	Number of sessions	Passing	No Fs	Ever logged on	Number of sessions	Passing	No Fs
Student	0.000	-0.099	0.008	-0.036	0.008	-0.123	-0.010	-0.033+
	(0.029)	(0.163)	(0.031)	(0.029)	(0.017)	(0.145)	(0.018)	(0.017)
Parent	0.064*	0.111	-0.007	-0.029	0.051**	0.075	0.007	-0.007
	(0.032)	(0.177)	(0.032)	(0.029)	(0.017)	(0.151)	(0.018)	(0.017)
Student+Parent	0.095**	0.259	-0.022	-0.040	0.080***	0.701**	0.057**	0.020
	(0.034)	(0.279)	(0.032)	(0.029)	(0.018)	(0.239)	(0.018)	(0.017)
Constant	0.082+	0.281	0.229***	0.456***	0.039	0.158	0.210***	0.501***
	(0.042)	(0.174)	(0.039)	(0.039)	(0.035)	(0.250)	(0.044)	(0.044)
Student Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.237	0.237	0.237	0.237	0.186	0.186	0.186	0.186
Observations	1162	1162	1162	1162	3601	3601	3601	3601

Notes. Our preferred model controls for student-level characteristics has a fixed effect for strata and uses cluster robust standard errors. Student Controls include dummy variables for gender, FRPL, special education status, Race/Ethnicity categories, and a missing indicator for Race/Ethnicity.

Standard errors in parentheses

+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

support. We show that strategic communications to students and their families can increase the likelihood that students take-up the resource by almost 50%—and more for struggling students—but the most effective treatment arm still only resulted in a quarter of students ever logging on to receive help from a tutor.

This study is among the first large-scale studies to document take-up of educational resources and opt-in tutoring during the pandemic (see also Kraft et al., 2022), and to quantify the differences between students who opt-in to using the resource and those who do not. Understanding who benefits from the provision of on-demand tutoring is key to understanding the potential of these resources to accelerate student learning (Geith & Vignare, 2008). Schools can offer opt-in tutoring to their entire student body at a fraction of the cost it would take to implement a more targeted resource during school time. Moreover, students can customize their opt-in tutoring experience to their specific needs (Reigeluth, 2014), and there is often no limit to how much a student can use the resource. As a result, on-demand tutoring has the potential to be high-impact if students choose to access tutors several times per week and the tutors are well trained and supported (Nickow et al., 2020; Robinson & Loeb, 2021). However, this flexibility and customization that on-demand tutoring affords also means that educators have less control over how and when students use the resource. Without targeted interventions, struggling students are unlikely to opt-in to the supports and will continue to fall behind as high achieving students benefit from the resource.

Our study also builds upon and extends the literature on using behavioral interventions in education. To date, the evidence on whether targeting behavioral interventions at students effectively improves student outcomes has been mixed (see Damgaard & Nielsen, 2018; Robinson et al., 2021). Prior studies have found evidence that behavioral interventions can

increase the take-up of optional educational resources (i.e., peer tutoring or coaching initiatives) for college students (Angrist et al., 2009; Paloyo et al., 2016; Pugatch & Wilson, 2018); but, the majority of these student-focused studies attempt to change the behaviors of students in college or planning to attend college (Castleman & Page, 2015; Oreopoulos & Petronijevic, 2018, 2019; Page et al., 2020; Page & Gehlbach, 2017). This study is one of the few focusing on impacting the educational behaviors of secondary students.

The study design allowed us to test the comparative and marginal benefits of targeting an intervention to both students and parents, as opposed to just one or the other. While strategic reminders and communications to parents consistently have positive impacts on students' educational behaviors (Bergman & Chan, 2021; Bergman et al., 2020; Chamberlain et al., 2021; Cortes et al., 2018; Doss et al., 2019; Kraft & Rogers, 2015; Lasky-Fink et al., 2021; Mayer et al., 2019; Robinson et al., 2022; Robinson, Lee, et al., 2018; Rogers & Feller, 2018; York et al., 2019), few have targeted students and parents simultaneously. An exception is a study by Castleman and Page (2017) that found no additional effect on college enrollment when providing reminders to parents and students, as opposed to just students. Our study, however, is the first to target both middle and high school students and their parents and explore secondary engagement and academic outcomes.

We found that sending communications to students alone did not increase the likelihood students used the resource and may have even resulted in worse course performance. Like prior studies, we found that communications to parents do positively impact student engagement behaviors (see Bergman, 2019; Lasky-Fink & Robinson, 2022). Sending communications to parents, as opposed to students, increased the likelihood students ever logged in to the tutoring platform but did not meaningfully increase the number of tutoring sessions students had overall,

nor did it translate into learning gains. However, students who received communications alongside their parents were most likely to take-up the resource and attend a greater number of sessions overall compared to all other conditions. Moreover, the effect of the communications was largest for students who struggled during the prior semester. This increase in usage of the on-demand tutoring platform also translated into students being more likely to pass their courses. If the goal is to encourage students to engage in beneficial educational behaviors, our findings suggest that we cannot rely on student agency alone—even as students mature and progress through secondary school. However, communicating relevant information to both students and parents can facilitate beneficial parent engagement throughout the K-12 schooling experience. Thus, a coordinated approach to engaging parents and students may be most effective at motivating positive educational behaviors and improving student outcomes.

The question of who accesses optional educational resources and how to increase access is only pressing if the resource benefits students. Exploiting the exogenous difference in take-up between experimental conditions, we found evidence that assignment to the most effective treatment arm led to a four percentage point increase in the likelihood students passed all their courses with grades that qualified for admission into the state university system. Our academic-focused analyses, however, are limited by the overall low take-up rate of on-demand tutoring by students overall and the quality of academic outcomes available.

Our results have immediate and broad implications for education policy. In the near-term, states and districts are spending billions of dollars to provide students and their families with resources to support learning after the disruptions to education (FutureEd, 2022). If the goal is to mitigate learning gaps for students who struggled the most, providing opt-in access to personalized tutoring and other educational resources is unlikely to help. These findings mirror

prior research showing that opt-out approaches (as opposed to those requiring students to opt-in) increase student participation in beneficial programs (Robinson, Pons, et al., 2018). Students will be much more likely to access these resources if they are embedded into their school learning experience. For instance, districts using on-demand tutoring services could provide teachers with directives and support to embed the use of the resource into their classroom activities and assigned homework. For students to benefit the most, however, schools should consider scheduling personalized, high-impact tutoring during the school day for students who need it most.

More broadly, the findings of this study point to the importance of further considering what access means in education. At the individual level, we know that families and students who have more means are more likely to seek out supplemental educational resources (Bacher-Hicks et al., 2021; Hansen & Reich, 2015). Given that marginalized students who come from low-income backgrounds and lack opportunity were most affected by the pandemic (Dorn et al., 2021), our results suggest that taking an opt-in approach to distributing educational resources is going to perpetuate inequality. At the organizational level, opt-in approaches may be equally inequitable. State education agencies are providing districts with a host of resources and trainings to support pandemic recovery efforts. For instance, the state education agencies across the country have developed comprehensive programs of offerings to support districts to develop tutoring programs (e.g., Rhode Island Department of Education, 2022). However, the districts who serve the most high-need students often have the least capacity to take advantage of these resources (Duke & VanGronigen, 2021).

The findings from this study suggest that we should not conflate open access with equity. Opt-in approaches are unlikely to address the persistent and increasing disparities in learning

between struggling students and their peers. Helping the students who need it most will require a coordinated effort between educators and families to provide students with embedded, personalized learning opportunities.

Methods

Our study received Institutional Review Board (IRB) approval from Brown University (IRB Protocol 2101002880) and is registered on the AEA RCT registry (AEA AEARCTR-0009710).

Data.

At the end of the school year, we received student-by-session platform usage data from the on-demand tutoring provider and student-level administrative data from the school district (including student-level demographic and academic data).

Demographics.

We collected student-level administrative data from the school district. We used the district indicators for gender (Female/Male/X, race/ethnicity (Asian/Black or African American/Hispanic/White/American Indian or Alaska Native/Native Hawaiian or Other Pacific Islander/Multi), eligibility for free and reduced priced lunch (FRPL; No/Yes), special education status (No/Yes), and primary home language (English/Spanish/Other).

Prior academic performance.

We used students' Fall 2020 course performance as a proximal measure of students' prior academic performance. Specifically, we used an indicator for whether a student passed all their Fall 2020 core courses with a C- or higher.

Engagement Outcomes.

We define take-up as logging on and having at least one session with a tutor that lasts more than one minute. We received data on the number of sessions students had over the course of the intervention period, as well as the number of messages they exchanged with their tutor. The number of messages exchanged constitutes the total number messages an individual student

sent to tutors during the entire intervention period. The intervention period started on February 11, 2022 and lasted throughout the end of the 2020-21 school year.

Academic Outcomes.

We created two indicators for whether students passed all their courses during the Spring 2021 semester. The indicators differ in the passing criteria based on pandemic-related policies. The first course credit indicator specifies whether a student passed all their core courses with a C- or higher (i.e., the standard district policy and the UC/CSU system minimum admission requirements). A course was considered part of the core curriculum if it fell under one of the following subjects: English Language Arts, Foreign Language, History/Social Studies, Math, or Science. The second course credit indicator denotes whether a student either received credit and/or passed all their courses with no Fs (i.e., the pandemic policy). Second, we calculated students' semester GPA in their core courses on a 4.0 scale (4 = A, 3.67 = A-, 3.33 = B+, etc.). As a result of Assembly Bill 104, many students chose to take the courses as pass/no pass and therefore effectively had no GPA for the Spring 2021 semester.

We created similar outcome variables for students' math courses in the Spring 2021 semester, measuring whether students' passed their math courses with a C- or higher, passed their math courses with no Fs, and math GPA for the Spring 2021 semester.

Randomized Controlled Trial Design and Procedure.

We partnered with Aspire to send communications to students and parents on behalf of the school to increase student usage of the on-demand tutoring platform during the Spring 2021 semester. We used the Qualtrics platform to send emails to the student body (and parents for whom we did not have a cell phone number) and text messages to parents. If the school did not

have a cell phone number listed for any guardian (2.25%), the parent received an email instead of a text message.

All students and their parents in the RCT sample received an initial communication on February 11, 2021. Students assigned to the control group or *Parent Only* treatment arm received a personalized email wishing them a good semester. Parents of students assigned to the control group or *Student Only* treatment arm received a similar personalized text message (or email) sending hopes that their child's semester was off to a good start and that they may receive updates about their child's school. This was the only communication these students and parents received as a part of the study. On the same day, students assigned to *Student Only* or *Student+Parent* treatment arms received an initial email that introduced the on-demand tutoring platform and provided information on how to access the platform along with a link. Parents assigned to *Parent Only* or *Student+Parent* treatment arms received either a two-part text message or an email introducing the platform and explaining how their child could log-on and get help from a tutor. For the remainder of the semester, students and parents assigned to receive communications received emails and text message, respectively.

Students and their parents who were assigned to receive communications also received a mailer as part of the intervention. These mailers were estimated to start arriving in mailboxes on February 23, 2021. For students assigned to the *Student+Parent* treatment arm, both students and parents received a mailing.

Analytic Strategy.

Our preferred specification for estimating the treatment effects of the intervention was:

$$Y_i = \alpha_0 + \beta_1 Treatment_i + \beta_2 PassFall20_i + \boldsymbol{\eta X_i} + \gamma_{jk} + \varepsilon_i \quad (1)$$

where Y_i is the outcome of interest for student *i*; *Treatment*$_i$ is an indicator variable coded to 0 for the control group, 1 for *Student Only*, 2 for *Parent Only*, and 3 for *Student+Parent*; *PassingFall20*$_i$ is an indicator for whether a student passed all their courses during the Fall 2020 semester with a C- or higher*;* $\boldsymbol{X_i}$ is a vector of student level controls (i.e., gender, race/ethnicity, FRPL, special education, and multi-language learners); γ_{jk} is a strata fixed effect (home language x grade level x school); and ε_i is an error term. We use robust standard errors.

To explore the heterogeneity of the treatment effect across subgroups, we interacted the relevant indicator variable with the treatment indicator. For instance, the equation looking at the treatment effect by students' Fall course performance was:

$$Y_i = \alpha_0 + \beta_1 Treatment_i + \beta_2 PassFall20_i + \beta_3 (Treatment\ x\ PassFall20)_i + \boldsymbol{\eta X_i} + \gamma_{jk} + \varepsilon_i$$

In addition to taking an intent-to-treat analysis looking at whether using on-demand tutoring impacts student academic outcomes, we conducted a treatment-on-the-treated analysis where we us student-level random assignment as an instrument for take-up of on-demand tutoring. For the first stage, we use a linear probability specification to model use of on-demand tutoring:

$$Takeup_i = \alpha_0 + \beta_1 Treatment_i + \beta_2 PassingFall20_i + \boldsymbol{\eta X_i} + \gamma_{jk} + \varepsilon_i \quad (3a)$$

where *Takeup*$_i$ is an indicator for whether a student ever logged on the tutoring platform. The second stage model uses a linear functional form as follows:

$$Y_i = \pi_0 + \pi_1 Takeup_i + \pi_2 PassingFall20_i + \boldsymbol{\eta X_i} + \gamma_{jk} + \varepsilon_i \quad (3b)$$

where Y_i represents an academic outcome, such as passing all courses. We instrument for each student's use of on-demand tutoring as described in equation 3a. The coefficient π_1 indicates the impact of using on-demand tutoring.

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