Financial Incentives, Health Screening, and Selection into Mental Health Care: Experimental Evidence from College Students in India*

Emily Breza Kevin Carney Vijaya Raghavan Kailash Rajah
Thara Rangaswamy Gautam Rao Frank Schilbach
Sobia Shadbar James Stratton

September 10, 2025

Abstract

High rates of depression and anxiety are prevalent among young adults globally, yet the majority do not seek mental health care. While financial incentives may increase treatment uptake, they risk wasting scarce resources by subsidizing care for individuals with low clinical need. We conducted a randomized controlled trial in Chennai, India (N=340) to test how modest financial incentives and personalized mental health feedback affect the uptake of free therapy among college students. Despite 56% of students screening positive for mild depression or anxiety, only 3% in the control group scheduled (and attended) an appointment. Offering a small cash incentive (∼$6 USD) for attending a therapy session increased appointments by 9 pp ($p = 0.06$) and slightly improved targeting. Providing personalized recommendations increased appointments by 10 pp ($p = 0.08$) among symptomatic students while reducing them among asymptomatic students, thus improving targeting. Combining cash incentives with personalized recommendations increased appointments by nearly 23 pp ($p < 0.01$) among symptomatic individuals, without inducing take-up by asymptomatic individuals. These findings suggest that low-cost financial incentives coupled with screening information can effectively increase the use of mental health services while targeting limited mental health care resources to those with greater need.

*We thank the team at the Behavioral Development Lab in Chennai for excellent research assistance. We received IRB approval from MIT, protocol #10924. This experiment was pre-registered at the AEA RCT registry (AEARCTR-0015379) and ClinicalTrials.gov (NCT06887569).

1 Introduction

A large share of young people face mental health challenges, yet take-up of mental health services is low in many parts of the world, especially in low-income countries (Wang et al., 2007; Patel et al., 2010; Mojtabai et al., 2011). While supply-side constraints are well documented (Patel et al., 2016; Alonso et al., 2018), there is growing evidence that demand-side factors also represent a significant barrier (Cronin et al., 2024; Roth et al., 2024). Interventions to increase mental health literacy and reduce stigma through education have shown limited success, particularly when it comes to behavioral change (Xu et al., 2018; Thornicroft et al., 2016). One potential policy tool to address these barriers is to offer cash incentives for anyone wanting to try therapy. The risk of this approach is undesirable selection: those most in need, such as individuals suffering from depression or anxiety, may have the least capacity to act in response to the incentives, due to symptoms of their condition. This may be particularly problematic if individuals are also poorly-informed of their own mental health status and the expected benefits of therapy. In this case, incentives might cause individuals without mental health care needs to wastefully consume scarce services.

We experimentally evaluate three interventions that aim to increase take-up and improve targeting of therapy among college students in Chennai, India. Our first intervention offers small cash rewards to any student who wants to try therapy. Rewards may increase take-up via standard price effects, by countering procrastination, underestimation of benefits, or providing social cover for using a stigmatized service. The second intervention instead uses a standard screening tool to inform students of their psychological distress levels and provides personalized recommendations regarding therapy. The motivating idea is that some people may not recognize the seriousness of their psychological distress, or may not realize that therapy is indicated as a treatment for the symptoms they are experiencing. Finally, a third treatment combines both cash rewards and screening, attempting to boost take-up while addressing the problem of adverse selection. We examine how these interventions

affect students' take-up of mental health services, as well as their effectiveness in targeting individuals most at risk.

We conduct our experiment in partnership with an all-women arts and science college in Chennai, India. We recruit our sample ($N = 340$) during college hours by visiting classrooms at times scheduled in coordination with the college administration.[1] Participants complete an online survey accessed via a link on their smartphones. The survey includes demographic questions, self-assessed mental health perceptions, prior treatment history, and the PHQ-ADS—a validated composite screening tool for depression and anxiety (Kroenke et al., 2019).

We document alarmingly high shares of mental distress at this college, mirroring recent evidence from India and around the world (Kumar et al., 2012; Yadav et al., 2016; Singh et al., 2017; Shah and Pol, 2020). Roughly half of students screen positive for at least mild symptoms of depression or anxiety, and around a quarter for moderate or severe symptoms.[2] Despite this, take-up of mental health services is very low: only 5% report currently receiving treatment from a mental health professional, even though counseling services at the college are available to students without charge. About 30% of students with moderate levels of depression or anxiety—for which psychotherapy is recommended as a treatment—do not think of themselves as having depression or anxiety.

We randomly assign students to a control condition or to one of three treatments. In the *Rewards* treatment, students receive a 500 rupee (∼6 USD) cash payment upon attending their first therapy. Students could complete this therapy session either with college counselors or with a partner mental health center that offered more specialized services off campus. In the *Screening* treatment, students receive personalized feedback on their PHQ-ADS results. In line with existing clinical guidelines in India, students with severe or moderate distress

[1] We pre-registered trying to reach all of the students in the college, but noted substantial uncertainty since we relied on the college to grant us time slots to meet students. Ultimately, we were able to reach only about 20 percent of the classrooms in the college before the semester ended.

[2] Future job prospects, academic stress, social isolation, relationship difficulties, and financial hardship are the most commonly reported sources of distress.

also received a recommendation to seek therapy, while those with mild or no distress did not receive a recommendation. In the *Rewards & Screening* treatment, students receive both interventions. All students, including in the control condition, have access to free therapy by qualified counselors at the college and an off-campus provider.

Our outcome measures focus on students' take-up of mental health services. Within the survey, we ask all students (including in the control condition) whether they would like to book or be contacted to schedule an appointment with a therapist at either the college or with an off-campus provider. We also acquire administrative data from the college counseling service and the partner mental health center to assess whether students attend at least one therapy session. As secondary outcomes, we also examine whether the interventions affect students' demand for related services, including a mental health app and additional support resources.

Only 3% of students in the control group make an appointment to see a therapist. This share is identical among symptomatic and asymptomatic students, suggesting little selection into therapy based on need in our sample population.[3] The *Rewards* treatment substantially increases take-up of therapy. Students offered a small cash incentive are on average 9 percentage points more likely to schedule a therapy appointment ($p = 0.06$). Students follow through on these appointments: they are 7 percentage points more likely to attend at least one therapy session (p = 0.09). While point estimates suggest larger increases in appointments for symptomatic students (11 pp) versus asymptomatic students (6 pp), this difference is not statistically significant. Contrary to fears that financial incentives might hurt targeting, we therefore find suggestive evidence of improved targeting.

The *Screening* intervention has no impact on take-up on average. However, this masks an important and sensible heterogeneity: it slightly reduces appointments made by asymp-

[3]Patients with higher symptom severity benefit more from psychotherapy (Bower et al., 2013), and better targeting is therefore valuable, particularly given the scarce supply of mental health services in India (Gururaj et al., 2016).

tomatic students, while substantially increasing appointments made by symptomatic students by 10 pp ($p = 0.08$). Thus, personalized feedback based on a screening tool induces take-up precisely among those with higher need.

In the combined *Rewards & Screening* intervention, there is a large aggregate effect on take-up (11 pp relative to the control group $p < 0.01$). Take-up is also 9 percentage points higher than in the *screening* intervention ($p = 0.07$) and similar to the *rewards* intervention ($p = 0.67$). The heterogeneity in effects is stark. There is a small and non-significant decrease in take-up among the asymptomatic, while take-up increases by 23 pp ($p < 0.01$) among symptomatic students. Thus, combining small cash rewards with screening information leads to a large increase in take-up, entirely driven by those in need. Treatment effects are 25 percentage points larger among symptomatic individuals compared to asymptomatic individuals ($p < 0.01$). This pattern holds not just for making appointments, but also for following through with visiting the therapist (19 pp, $p < 0.01$).

Our paper speaks to a growing literature on the economics of mental health. Existing studies have documented the significant negative impacts of mental health problems on a range of economic outcomes, including labor market outcomes and educational attainment (Currie and Stabile, 2006; Ridley et al., 2020; Biasi et al., 2021). Recent randomized evaluations have demonstrated that interventions designed to improve mental health, including mental health therapy or counseling, can yield substantial improvements in mental health and other outcomes (Patel et al., 2017; Baranov et al., 2020; Bhat et al., 2022). Despite these potential benefits, take-up rates remain stubbornly low due to both supply- and demand-side constraints. On the demand side, information frictions and stigma are significant barriers that prevent individuals from seeking care (Cronin et al., 2024; Roth et al., 2024; Smith, 2025). Our study contributes to this literature by explicitly testing interventions designed to alleviate both financial and informational barriers, evaluating their effectiveness in enhancing take-up and targeting individuals most at risk.

We also contribute to the literature on take-up and targeting of social programs, particularly in developing-country contexts. Prior work highlights barriers that prevent individuals from accessing beneficial services, such as a lack of information (Roth et al., 2024), administrative complexity (Coombs et al., 2021), and stigma associated with program participation (Bharadwaj et al., 2017). Alatas et al. (2012) demonstrate how community screening mechanisms significantly improve the targeting efficiency of social welfare programs, ensuring that resources reach those most in need, while Naik (2025) finds that individuals with poor mental health are more responsive both to benefits and barriers to take-up of social welfare programs relative to those with good mental health. Our research extends these insights, demonstrating how self-screening interventions can be used to improve the allocation of individuals to social programs. Our work also connects to a broader literature in health economics studying selection into engagement with health services and health insurance (*e.g.*, Einav and Finkelstein, 2011; Hackmann et al., 2012).

2 Setting and Experimental Design

The experiment was designed with two broad objectives. First, we aim to measure the effect of financial incentives on people's pursuit of treatment from mental healthcare professionals (psychotherapy from therapists/counselors, in particular). Second, we aim to understand the effects of providing people with information on their current mental health status (specifically, about their current experiences of psychological distress as determined by their PHQ-ADS score) on their pursuit of therapy. This outcome is of particular interest to understand these effects in individuals with poorer mental health outcomes. We assess the impacts of these interventions on different stages of treatment pursuit, from initial expression of interest to varying degrees of measurable action, including (i) interactions with counselors via WhatsApp messages, (ii) scheduling appointments, and (iii) attendance of appointments.

2.1 Context

India is an especially relevant context for the study because of low existing take-up: India's National Mental Health Survey reports that five-sixths of individuals with depression do not receive appropriate care (Gururaj et al., 2016). In addition to this, in recent surveys of Indian college students, between 50% and 70% of students have screened positive for depression, with similar shares for anxiety (Kumar et al., 2012; Yadav et al., 2016; Singh et al., 2017; Shah and Pol, 2020). College can be an especially challenging time for youth in this setting, as students transition away from tight-knit family environments towards spending considerable time around new peer groups and face a challenging labor market.[4] Most college students in India do not work while studying,[5] limiting their financial independence and making it difficult to access therapy without parental support—support they may not receive due to prevailing social norms around mental health. While attitudes among younger cohorts are shifting, stigma around seeking mental health care remains widespread (Gaiha et al., 2020).

2.2 Sample recruitment

We recruited 340 undergraduate students from an all-women's arts and science college in Chennai. Enrollment took place at the classroom level on a rolling basis. Students received an introduction to the study by the research team. Students who were within the eligible age range (18 to 30) and who consented to the study completed a survey on their personal mobile devices, including questions on demographics, self-perceived mental health, treatment history. The survey also included the PHQ-ADS, a 16-point validated composite instrument screening for depression and anxiety.

[4]Indeed, a survey of students in 19 colleges around eight countries indicates that "colleges around the world are contending with rising rates of mental disorders, and in many cases, the demand for services on campus far exceeds the available resources' (Auerbach et al., 2018, p. 623).

[5]In our sample of college students, around 45% report having no personal disposable income at all.

2.3 Experimental design

Figure 1 presents our simple two-by-two cross-randomization design. We use a simple two-by-two cross-randomization design. Randomization of participants into a control group or one of the three treatment groups is done within the survey instrument at the individual level, stratified by participants' PHQ-ADS scores collected in the baseline (pre-treatment) section of the survey. All participants (a) watched a video introducing them to the mental health services available in the college, including introductory videos of the college counselors, (b) had access to therapy at no cost for the duration of the study via their college counselors and additionally at SCARF, a mental health center in Chennai, (c) received links to prefilled WhatsApp messages to each of the study affiliated counselors to request a therapy session, (d) received links to download a mental health app and/or web articles on depression and anxiety, if they indicated they were interested in receiving these resources.

In addition, the treatment group received the following interventions:

1. **Rewards:** Participants in the *Rewards* group receive a cash payment of Rs. 500 (∼USD 6) for attending their first therapy session with a study-affiliated counselor.

2. **Screening:** Participants in the *Screening* group received feedback on whether their responses to the PHQ-ADS questions fit in the standard risk categories of no, mild, moderate, or severe distress. Students whose PHQ-ADS scores indicated moderate or severe symptoms of depression or anxiety received a recommendation to make an appointment with a counselor based on their score.

3. **Rewards and Screening:** Participants in this group receive both the rewards and screening interventions described above.

Appendix Figure 1 displays an example of the information provided to students as part of the survey. The figure displays information about booking counseling and the messages provided on a student's PHQ-ADS category, which was revealed to students in the *Screening*

and *Rewards and Screening* groups. The figure also displays the information on incentives provided to students in the *Rewards* and *Rewards and Screening* groups.

Participants who consented to receive further communications from the research team were sent nudge messages one day, seven days, and 21 days after survey completion thanking them for their participation in the research and reminding them of the mental healthcare services being offered as part of the study and how they could be accessed, as well as reminding participants in the *Incentive* groups of their eligibility to receive cash rewards for attending their first therapy session with a study affiliated counselor.

For ethical reasons, participants with PHQ-ADS scores of 30 or above—indicating severe risk of depression and anxiety—in the non-screening treatment arms are also informed of their scores at the end of the survey. For outcome variables measured within the survey, these participants remain part of the group to which they were randomly assigned. One outcome variable (completing the process to make an appointment for therapy) is measured after the conclusion of the participant survey. For this outcome variable, we separately run regressions both including and excluding these individuals.

Appendix Table 1 shows balance tests of baseline characteristics across treatments. Baseline characteristics are generally similar across control arms. There is some imbalance on personal income, which is included as one of the controls throughout the analysis.

2.4 Outcome measures

The primary outcomes of this study are the pursuit of psychotherapy and other alternative care interventions for mental health. We measured this in a staggered manner with differential levels of interest and intent being recorded at two stages: immediately post treatment during the survey, and a short period post survey completion.

Initiating engagement. We measure several steps towards engagement with mental

health services:

1. *Contact with counselors.* Within the initial survey, students can message study-affiliated counselors via WhatsApp, and/or request that a study-affiliated counselor contact them to discuss mental health and therapy. For simplicity, our main analysis uses an indicator variable for a participant initiating engagement in either of these ways. We also report results for these two outcomes separately.

2. *Making appointment.* We measured whether participants actually made an appointment with a study-affiliated counselor by tracking administrative records from the counseling offices for a period of 60 days post survey completion.

3. *Interest in mental-healthcare app.* We recorded participants' choice to click a link to learn more about accessing a mental health-related app as part of the survey.

4. *Interest in information about mental health.* We recorded participants' choice to click a link to gain more information about mental health and therapy.

Actual Take-up. Beyond recording interest, we also measure whether participants use mental health services

1. *Accessing mental-healthcare app:* We recorded participants' clicks on trackable links to the mental-healthcare app provided in the survey.

2. *Accessing mental-healthcare literature:* We recorded participants' clicks on trackable links to mental-healthcare literature (articles on depression and anxiety) provided in the survey, conditional upon their interest.

3. *Attending therapy sessions:* We measured whether participants actually attended a scheduled appointment with a study-affiliated counselor by tracking administrative records from the counseling offices for a period of 60 days post survey completion. We also measured the total number of sessions attended using the same data.

2.5 Baseline mental health

Figure 2 shows various indicators of students' mental health at baseline. Panel (a) displays the distribution of PHQ-ADS scores. A little over half of students screen for depression or anxiety (PHQ scores of at least 10); around a quarter of students screen for moderate (PHQ scores between 20 and 29) or severe (PHQ scores of 30 or above) depression or anxiety. This high incidence of depression and anxiety is consistent with other recent surveys of mental health at Indian colleges (Kumar et al., 2012; Yadav et al., 2016; Singh et al., 2017; Shah and Pol, 2020).

Panel (b) shows students' self-assessed mental health. Around one third of students self-assess as currently having depression; the share self-assessing as currently having anxiety is a little lower. One-sixth of students indicate that they believe they have both conditions. Around half of students indicate that they do not have either condition.

Panel (c) compares students' self-assessed mental health to PHQ-ADS scores. PHQ-ADS scores are strongly correlated with the likelihood that a student believes that she has depression or anxiety (pairwise correlation = 0.43, $p < 0.01$). Nonetheless, panel (c) also demonstrates that around 51% of students who screen for mild depression or anxiety on the PHQ-ADS do not believe they are suffering from depression or anxiety, and around 25% of students who screen for moderate or severe depression or anxiety do not believe they are suffering from either condition. When interpreting this relationship, we emphasize that there are reasons for self-assessment to differ from PHQ-ADS scores other than mis-classification: for instance, the PHQ-ADS is itself a noisy measure of mental health. Nonetheless, panel (c) suggests that there is some room for students' beliefs to be affected by learning their PHQ-ADS scores, at least in the sense that their beliefs about their well-being do not fully predict PHQ-ADS scores.

Panel (d) presents the major stated reasons for mental distress among students screening for depression and/or anxiety. The most common reasons for distress are future job/career

prospects (62% of students), academic matters (49%), and feelings of isolation (38%).

Despite this high incidence, Appendix Figure 2 shows that there is very little engagement with mental health services at baseline. Panel (a) shows that only around 10% of students have any prior experience with counselors or psychologists, and only around 5% of students are currently seeing a counselor or psychologist. This limited engagement does not appear to be driven by beliefs about the inefficacy of therapy: around three-quarters of students state that they believe therapy would be very or extremely helpful in improving their well-being or quality of life (Panel (b)). Panel (c) shows that the most common stated reasons not to take up therapy—among students who screen for depression or anxiety, and who do not indicate interest in therapy—are a student's belief that they do not need therapy, that therapy will not help them, or that they do not know how therapy works.

3 Results

Average effects. We begin by assessing the total effects of treatment assignment. We run OLS regressions of the form

$$\mathrm{Y}_i = \alpha + \beta \mathrm{Screen}_i + \gamma \mathrm{Rewards}_i + \delta(\mathrm{Screen\ and\ rewards}_i) + X_i'\lambda + \epsilon_i, \tag{1}$$

where Y_i represents the outcomes for individual i described above, and X_i is a vector of controls for consisting of fixed effects for categories of PHQ-ADS scores, family support for seeing a therapist, self-reported current mood, mood over the last two weeks, and mood over the last six months, self-reported current and past experiences of depression and anxiety, and level of disposable income.

Table 1 Panel A displays regression coefficients from this specification. At baseline, the level of engagement with mental health services is low: although almost 19% of students initiate contact with study counselors, only about 3% schedule or attend appointments.

For each of the four outcome variables, the estimated effect of assignment to the screening group (β) is statistically indistinguishable from zero. Though the estimate is imprecise, we are able to rule out large effects of screening on average: for instance, we can conclude at the 5% level that the effect of screening on likelihood of attending an appointment was no more than 6 p.p.

By contrast, financial incentives increase average engagement with mental health services. The estimated effect of assignment to the *Rewards* group (γ) is positive in all specifications, and significant for the first three outcomes. Rewards nearly double students' interest in counselor contact (0.34 vs. 0.19, col. 1), and they triple the scheduling a therapy appointment (0.12 vs. 0.03, col. 2). Remarkably, these impacts nearly entirely translate into attendance of therapy appointments (col. 3). The estimated effect of assignment to the combined screening and rewards group (δ) is of similar magnitude and statistically indistinguishable from the corresponding estimates for the rewards group.[6]

Heterogeneity by baseline mental health status. We now turn to heterogeneity by participants' baseline mental health status, as measured by their PHQ-ADS scores. Table 1 Panel B displays regression coefficients from the equation

$$\begin{aligned} \mathrm{Y}_i = \alpha_0 &+ \alpha_1 \mathrm{Symptomatic}_i + \beta_0 \mathrm{Screen}_i + \beta_1 \mathrm{Screen}_i \times \mathrm{Symptomatic}_i \\ &+ \gamma_0 \mathrm{Rewards}_i + \gamma_1 \mathrm{Rewards}_i \times \mathrm{Symptomatic}_i \\ &+ \delta_0 (\mathrm{Screen\ and\ rewards}_i) + \delta_1 (\mathrm{Screen\ and\ rewards}_i) \times \mathrm{Symptomatic}_i \\ &+ X_i' \lambda + \epsilon_i, \end{aligned} \tag{2}$$

where $\mathrm{Symptomatic}_i$ is an indicator variable for student i having a PHQ-ADS score of at least

[6]Appendix Table 2 shows the results from a corresponding regression which treatments to compare all students who received rewards (either in the rewards group or in the rewards plus screening group) *vs.* all students who did not receive rewards (either in the pure control group or in the screening group), and likewise for all students who did *vs.* did not receive screening. We interpret these pooled treatment effect of assignment to a given treatment arm as being conditional on the assignment of other treatment arms in the experiment (Kremer 2003; Duflo et al. 2007; Muralidharan et al. 2025). The results are similar to those in Table 1: rewards robustly increase average engagement with mental health services; screening does not tend to affect average engagement.

10. This specification enables us to separately estimate treatment effects for symptomatic and asymptomatic students. For instance, we interpret β_0 as the causal effect of assignment to the *Screening* group on the outcome variable among students who are asymptomatic, and $\beta_0 + \beta_1$ as the causal effect among students who are symptomatic.

At baseline, we find limited evidence of selection into treatment based on symptom severity, as indicated by the comparison of control means: students with higher PHQ-ADS scores are more likely to engage with mental health services, as measured by each of the three outcome variables. For instance, around 5% of students who do not screen for depression or anxiety initiate contact with counselors; the share is around 30% among students who screen for depression or anxiety. The degree of self-selection is much smaller for scheduling and attending appointments: only a very small number of students either schedule or attend appointments, even when restricting attention to symptomatic students.

While leaving average engagement with mental health services unchanged, the *Screening* treatment appears to *reallocate* engagement between individuals, as shown in the first two rows of Table 1 Panel B. The *Screening* has a small negative effect on asymptomatic students, but a positive effect on asymptomatic students. By contrast, assignment to the *Rewards* treatment increases the level of engagement with mental health services, without substantially affecting the difference between students with differing levels of symptoms. Finally, assignment to the *Rewards and Screening* treatment increases take-up among symptomatic individuals without affecting take-up among asymptomatic students. The effects are large in magnitude. For instance, assignment to the rewards and screening group increases the likelihood of scheduling an appointment by 23 percentage points for symptomatic students—a substantial change relative to the control mean of 4 percentage points.

Figure 3a visualizes these effects. Navy bars display the likelihood of scheduling counseling among asymptomatic students, separately for each of the four treatment arms. Light blue bars display the likelihood of scheduling counseling among symptomatic students in each

treatment arm. The panel also displays 90% confidence intervals for the light blue bars. Assignment to rewards tends to increase engagement with mental health services among all students; assignment to screening increases engagement with mental health services only among symptomatic students.

Figure 3b visualizes the effects using a continuous PHQ-ADS score, rather than the discrete categories in Table 1. The figure presents a binned scatterplot of the likelihood of scheduling counseling vs. PHQ-ADS scores, separately for each of the four treatment lines. Dots represent deciles of the data; we also present lines of best fit from the regression:

$$\begin{aligned}\text{Appointment scheduled}_i = \alpha_0 + \alpha_1 \text{PHQ-ADS}_i + \beta_0 \text{Screen}_i + \beta_1 \text{Screen}_i \times \text{PHQ-ADS}_i \\ + \gamma_0 \text{Rewards}_i + \gamma_1 \text{Rewards}_i \times \text{PHQ-ADS}_i + \\ + \delta_0 \text{Screen and rewards}_i + \delta_1 \text{Screen and rewards}_i \times \text{PHQ-ADS}_i + \epsilon_i.\end{aligned} \tag{3}$$

In the navy blue line, representing the pure control group, very few students schedule therapy, regardless of their PHQ-ADS score: as a result, the slope of the relationship between the likelihood of scheduling counseling and PHQ-ADS score in the control group is very close to zero. The *Rewards* treatment, presented in light blue, produces a level shift in interest in undertaking therapy: all students are more likely to schedule counseling. By contrast, the screening group, presented in orange, produces a pivot relative to the control group: students at high levels of PHQ-ADS scores are more likely to schedule therapy, whereas there is no effect (or even a marginally negative effect) for students with low PHQ-ADS scores. The rewards plus screening line, in maroon, maintains both the pivot effect of the screening group, and the level increase of the rewards group.

Figure 3 shows treatment effects splitting the sample into those whose self-assessed mental health status matched the results of the PHQ-ADS test (Panel A) and those whose self-assessments did not match (Panel B). We find significant positive impacts of screening on appointment scheduling among students who self-assessed as being symptomatic and

registered symptomatic on the PHQ-ADS ($p < 0.01$). The results suggest that the value of screening extends beyond correcting a basic misperception of one's mental health status. Instead, the benefit is likely to come from the reinforcement provided by the screening information and the recommendation to seek therapy.

4 Discussion and Conclusion

Psychotherapy is an effective treatment for depression/anxiety (Cuijpers et al., 2013, 2023; Barth et al., 2016; Bhat et al., 2022), but take-up remains low. For this reason, it is a policy priority in many parts of the world to increase engagement with mental health services (Patel and Prince, 2010). In light of the scarcity of supply of mental health services, these policies face the challenge of increasing take-up while prioritizing need.

We studied this challenge in a sample of college students in Chennai. A small financial incentive substantially increased engagement with mental health services, including a four-fold increase in the likelihood of scheduling a therapy appointment. However, combining screening information with incentives can improve the targeting of mental health resources and generate large gains in take-up among the population with the greatest need. Moreover, the effects are strongest within the group of symptomatic individuals who also self-assess as having depression or anxiety. These findings raise a series of open questions. For example, how would the results compare in other samples in developing countries? Our study population of college students exhibits high awareness of mental health disorders, though low perceived usefulness of therapy.

References

Alatas, Vivi, Abhijit Banerjee, Rema Hanna, Benjamin A Olken, and Julia Tobias (2012), "Targeting the poor: evidence from a field experiment in indonesia." *American Economic Review*, 102, 1206–1240.

Alonso, Jordi, Zhaorui Liu, Sara Evans-Lacko, Ekaterina Sadikova, Nancy Sampson, Somnath Chatterji, Jibril Abdulmalik, Sergio Aguilar-Gaxiola, Ali Al-Hamzawi, Laura H Andrade, et al. (2018), "Treatment gap for anxiety disorders is global: Results of the world mental health surveys in 21 countries." *Depression and anxiety*, 35, 195–208.

Auerbach, Randy P, Philippe Mortier, Ronny Bruffaerts, Jordi Alonso, Corina Benjet, Pim Cuijpers, Koen Demyttenaere, David D Ebert, Jennifer Greif Green, Penelope Hasking, et al. (2018), "Who world mental health surveys international college student project: Prevalence and distribution of mental disorders." *Journal of abnormal psychology*, 127, 623.

Baranov, Victoria, Sonia Bhalotra, Pietro Biroli, and Joanna Maselko (2020), "Maternal depression, women's empowerment, and parental investment: Evidence from a randomized controlled trial." *American economic review*, 110, 824–859.

Barth, Jürgen, Thomas Munder, Heike Gerger, Eveline Nüesch, Sven Trelle, Hansjörg Znoj, Peter Jüni, and Pim Cuijpers (2016), "Comparative efficacy of seven psychotherapeutic interventions for patients with depression: a network meta-analysis." *Focus*, 14, 229–243.

Bharadwaj, Prashant, Mallesh M Pai, and Agne Suziedelyte (2017), "Mental health stigma." *Economics Letters*, 159, 57–60.

Bhat, Bhargav, Jonathan De Quidt, Johannes Haushofer, Vikram H Patel, Gautam Rao, Frank Schilbach, and Pierre-Luc P Vautrey (2022), "The long-run effects of psychotherapy on depression, beliefs, and economic outcomes." Technical report, National Bureau of Economic Research.

Biasi, Barbara, Michael S Dahl, and Petra Moser (2021), "Career effects of mental health." Technical report, National Bureau of Economic Research.

Bower, Peter, Evangelos Kontopantelis, Alex Sutton, Tony Kendrick, David A Richards, Simon Gilbody, Sarah Knowles, Pim Cuijpers, Gerhard Andersson, Helen Christensen, et al. (2013), "Influence of initial severity of depression on effectiveness of low intensity interventions: meta-analysis of individual patient data." *Bmj*, 346.

Coombs, Nicholas C, Wyatt E Meriwether, James Caringi, and Sophia R Newcomer (2021), "Barriers to healthcare access among us adults with mental health challenges: A population-based study." *SSM-population health*, 15, 100847.

Cronin, Christopher J, Matthew P Forsstrom, and Nicholas W Papageorge (2024), "What good are treatment effects without treatment? mental health and the reluctance to use talk therapy." *Review of Economic Studies*, rdae061.

Cuijpers, Pim, Matthias Berking, Gerhard Andersson, Leanne Quigley, Annet Kleiboer, and Keith S Dobson (2013), "A meta-analysis of cognitive-behavioural therapy for adult depression, alone and in comparison with other treatments." *The Canadian Journal of Psychiatry*, 58, 376–385.

Cuijpers, Pim, Clara Miguel, Mathias Harrer, Constantin Yves Plessen, Marketa Ciharova, David Ebert, and Eirini Karyotaki (2023), "Cognitive behavior therapy vs. control conditions, other psychotherapies, pharmacotherapies and combined treatment for depression: A comprehensive meta-analysis including 409 trials with 52,702 patients." *World Psychiatry*, 22, 105–115.

Currie, Janet and Mark Stabile (2006), "Child mental health and human capital accumulation: the case of adhd." *Journal of health economics*, 25, 1094–1118.

Duflo, Esther, Rachel Glennerster, and Michael Kremer (2007), "Using randomization in development economics research: A toolkit." *Handbook of development economics*, 4, 3895–3962.

Einav, Liran and Amy Finkelstein (2011), "Selection in insurance markets: Theory and empirics in pictures." *Journal of Economic perspectives*, 25, 115–138.

Gaiha, Shivani Mathur, Tatiana Taylor Salisbury, Mirja Koschorke, Usha Raman, and Mark Petticrew (2020), "Stigma associated with mental health problems among young people in india: a systematic review of magnitude, manifestations and recommendations." *BMC psychiatry*, 20, 1–24.

Gururaj, G., M. Varghese, V. Benegal, G. N. Rao, K. Pathak, L. K. Singh, R. Y. Mehta, D. Ram, T. M. Shibukumar, A. Kokane, R. K. Lenin Singh, B. S. Chavan, P. Sharma, C. Ramasubramanian, P. K. Dalal, P. K. Saha, S. P. Deuri, A. K. Giri, A. B. Kavishvar, V. K. Sinha, J. Thavody, R. Chatterji, B. S. Akoijam, S. Das, A. Kashyap, V. S. Ragavan, S. K. Singh, R. Misra, and NMHS Collaborators Group (2016), "National mental health survey of india, 2015-16: Mental health systems." Technical report, National Institute of Mental Health and Neuro Sciences. NIMHANS Publication No. 130.

Hackmann, Martin B, Jonathan T Kolstad, and Amanda E Kowalski (2012), "Health reform, health insurance, and selection: Estimating selection into health insurance using the massachusetts health reform." *American Economic Review*, 102, 498–501.

Kremer, Michael (2003), "Randomized evaluations of educational programs in developing countries: Some lessons." *American Economic Review*, 93, 102–106.

Kroenke, Kurt, Fitsum Baye, and Spencer G Lourens (2019), "Comparative validity and responsiveness of phq-ads and other composite anxiety-depression measures." *Journal of affective disorders*, 246, 437–443.

Kumar, Ganesh S, Animesh Jain, and Supriya Hegde (2012), "Prevalence of depression and its associated factors using beck depression inventory among students of a medical college in karnataka." *Indian journal of Psychiatry*, 54, 223–226.

Mojtabai, Ramin, Mark Olfson, Nancy A Sampson, Robert Jin, Benjamin Druss, Philip S Wang, Kenneth B Wells, Harold A Pincus, and Ronald C Kessler (2011), "Barriers to mental health treatment: results from the national comorbidity survey replication." *Psychological medicine*, 41, 1751–1761.

Muralidharan, Karthik, Mauricio Romero, and Kaspar Wüthrich (2025), "Factorial designs, model selection, and (incorrect) inference in randomized experiments." *Review of Economics and Statistics*, 1–16.

Naik, Canishk (2025), "Mental health and the targeting of social assistance." Technical report, Working Paper.

Patel, Vikram, Mario Maj, Alan J Flisher, Mary J De Silva, Mirja Koschorke, Martin Prince, WPA Zonal, Member Society Representatives, Raymond Tempier, Michelle Riba, Mauricio Sanchez, et al. (2010), "Reducing the treatment gap for mental disorders: a wpa survey." *World Psychiatry*, 9, 169–176.

Patel, Vikram and Martin Prince (2010), "Global mental health: a new global health field comes of age." *Jama*, 303, 1976–1977.

Patel, Vikram, Benedict Weobong, Helen A Weiss, Arpita Anand, Bhargav Bhat, Basavraj Katti, Sona Dimidjian, Ricardo Araya, Steve D Hollon, Michael King, et al. (2017), "The healthy activity program (hap), a lay counsellor-delivered brief psychological treatment for severe depression, in primary care in india: a randomised controlled trial." *The Lancet*, 389, 176–185.

Patel, Vikram, Shuiyuan Xiao, Hanhui Chen, Fahmy Hanna, AT Jotheeswaran, Dan Luo, Rachana Parikh, Eesha Sharma, Shamaila Usmani, Yu Yu, et al. (2016), "The magnitude of and health system responses to the mental health treatment gap in adults in india and china." *The Lancet*, 388, 3074–3084.

Ridley, Matthew, Gautam Rao, Frank Schilbach, and Vikram Patel (2020), "Poverty, depression, and anxiety: Causal evidence and mechanisms." *Science*, 370, eaay0214.

Roth, Christopher, Peter Schwardmann, and Egon Tripodi (2024), "Misperceived effectiveness and the demand for psychotherapy." *Journal of Public Economics*, 240, 105254.

Shah, Tanvi Deepak and Titiksha Pol (2020), "Prevalence of depression and anxiety in college students." *Journal of Mental Health and Human Behaviour*, 25, 10–13.

Singh, Manjot, Naveen Krishan Goel, Manoj Kumar Sharma, and Ravleen Kaur Bakshi (2017), "Prevalence of depression, anxiety and stress among students of punjab university, chandigarh." *National Journal of Community Medicine*, 8, 666–671.

Smith, Emma (2025), "Stigma and social cover: A mental health careexperiment in refugee networks." Working paper.

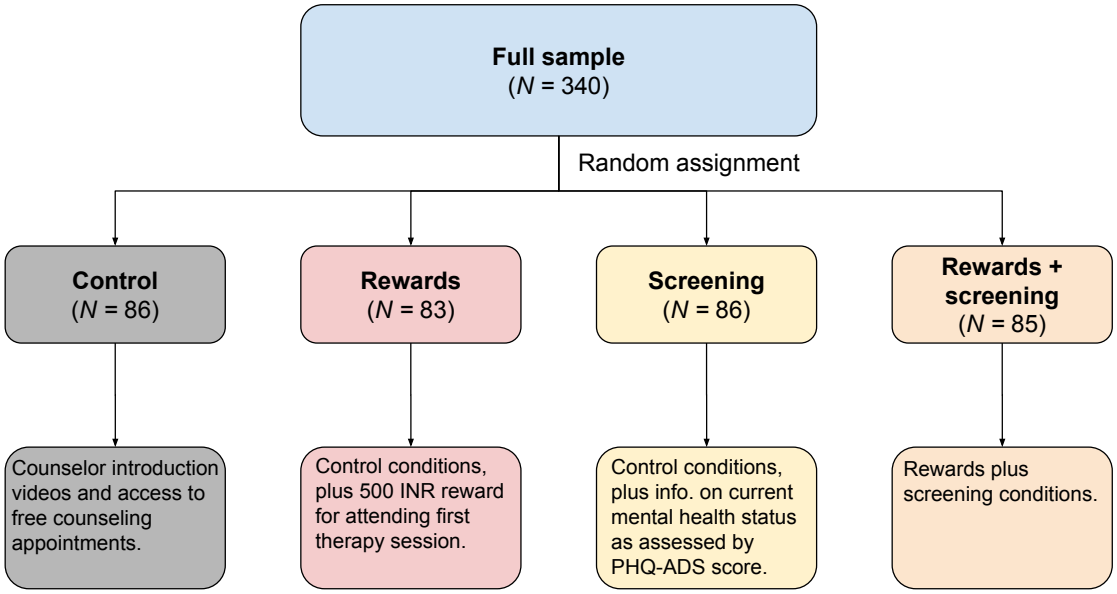
Thornicroft, Graham, Nisha Mehta, Sarah Clement, Sara Evans-Lacko, Mary Doherty, Diana Rose, Mirja Koschorke, Rahul Shidhaye, Claire O'Reilly, and Claire Henderson (2016), "Evidence for effective interventions to reduce mental-health-related stigma and discrimination." *The Lancet*, 387, 1123–1132.

Wang, Philip S, Sergio Aguilar-Gaxiola, Jordi Alonso, Matthias C Angermeyer, Guilherme Borges, Evelyn J Bromet, Ronny Bruffaerts, Giovanni De Girolamo, Ron De Graaf, Oye Gureje, et al. (2007), "Use of mental health services for anxiety, mood, and substance disorders in 17 countries in the who world mental health surveys." *The Lancet*, 370, 841–850.

Xu, Ziyan, Fangfang Huang, Markus Koesters, Tobias Staiger, Thomas Becker, Graham Thornicroft, and Nicolas Ruesch (2018), "Effectiveness of interventions to promote help-seeking for mental health problems: systematic review and meta-analysis." *Psychological medicine*, 48, 2658–2667.

Yadav, Rashmi, Shubhanshu Gupta, and Anil K Malhotra (2016), "A cross sectional study on depression, anxiety and their associated factors among medical students in jhansi, uttar pradesh, india." *Int J Community Med Public Health*, 3, 1209–14.

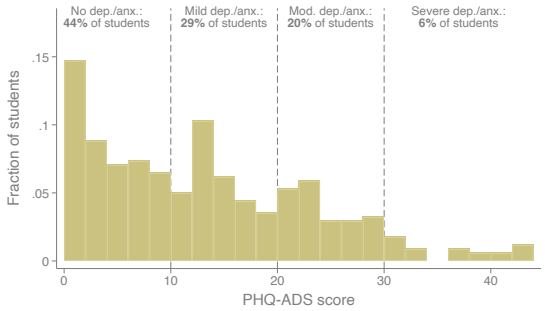
Figure 1: Experimental design



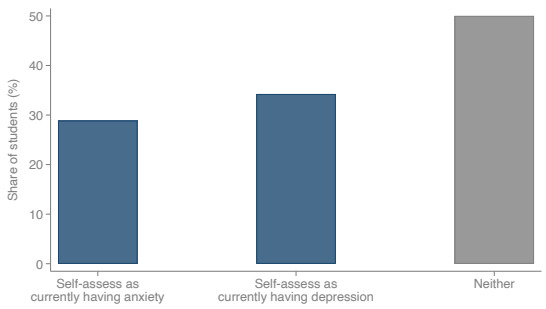
Notes: This figure presents the experimental design. For ethical reasons, we also provide screening results to students who are randomized to the control or rewards groups but screen for severe depression or anxiety (see Section 2.3).

Figure 2: Mental health status at baseline

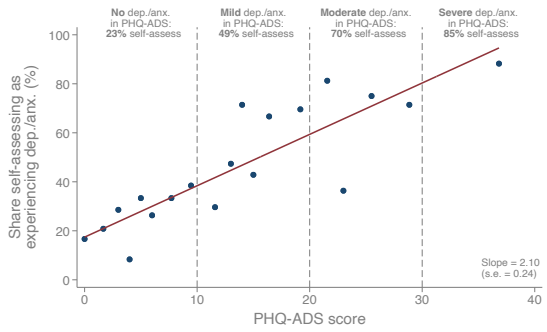
(a) Distribution of PHQ-ADS Scores



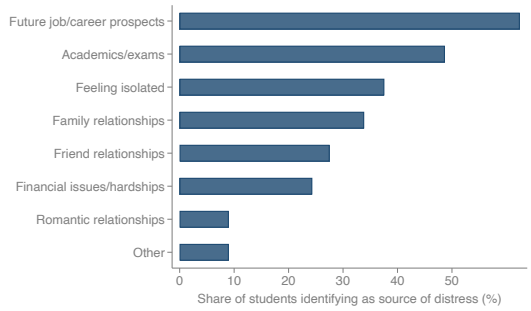
(b) Self-assessed mental health



(c) Current self-assessment *vs.* PHQ-ADS scores



(d) Sources of distress among students screening for depression or anxiety



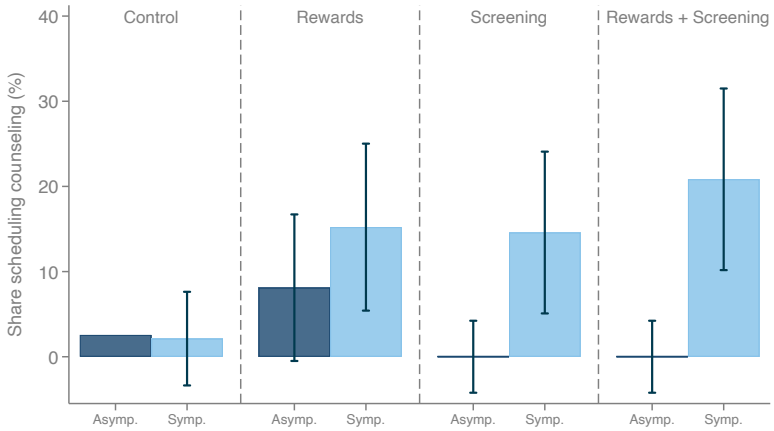
Notes: Panel (a) presents a histogram of PHQ-ADS scores at baseline. The text indicates the share of students screening for no depression or anxiety (PHQ-ADS score strictly of 9 or below), mild depression or anxiety (PHQ-ADS score between 10 and 19), moderate depression or anxiety (PHQ-ADS score between 20 and 29) and severe depression or anxiety (PHQ-ADS score of 30 or above). Panel (b) presents a bar chart of students' self-assessment of their current mental health. Note that bars do not add up to 100% because students can be in multiple navy bars. Panel (c) shows a binned scatterplot of the likelihood that a student self-assesses as experiencing depression or anxiety *vs.* the student's PHQ-ADS score. Ventiles of the data are presented as navy dots; the red line is a line of best fit (estimated on the microdata). The bottom right of the figure displays the point estimate and standard error on β in an OLS regression of the form

$$\text{Self-assess}_i = \alpha + \beta \text{PHQ-ADS}_i + \epsilon_i.$$

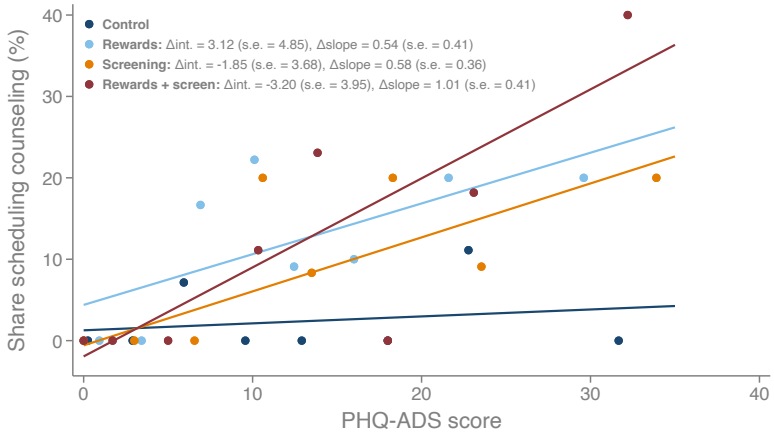
Panel (d) presents a bar chart of the sources of distress among students, restricting attention to students who screen for depression or anxiety (PHQ-ADS score of at least 10). Note that bars do not add up to 100% because students can be in multiple bars.

Figure 3: Effects of treatment assignment on likelihood of scheduling counseling, by baseline mental health status

(a) Effects by symptomatic status



(b) Effects by PHQ-ADS score



Notes: This figure shows the likelihood of scheduling counseling by baseline mental health status in each treatment arm. In panel (a), navy bars show the likelihood of scheduling counseling for asymptomatic individuals (PHQ-ADS ≤ 9) in each treatment arm, and light blue bars for symptomatic individuals (PHQ-ADS ≥ 10). Black bars show 90% confidence intervals relative to the control asymptomatic mean, computed using regression specification (2). For instance, the 90% confidence interval on the "screening, symptomatic" bar corresponds to the point estimate for α_0, plus the 90% confidence interval for the value of $\alpha_1 + \beta_0 + \beta_1$.

Panel (b) presents a binned scatterplot. Each navy dot represents a decile of the control group. The navy line is a line of best fit (estimated on the microdata). The orange, light blue, and maroon series replicate the navy series for the rewards, screening, and rewards plus screening groups, respectively. The text reports regressions of (3). The navy text reports estimates of α_0 (as the intercept term) and α_1 (the slope term), with corresponding standard errors. The orange text reports estimates of β_0 and β_1. The light blue text reports estimates of γ_0 and γ_1. The maroon text reports estimates of δ_0 and δ_1.

Table 1: Effects of saturated treatment assignment on primary outcomes

	Total interest in counselor contact (1)	Scheduled Appointment (2)	Attended Appointment (3)	Scheduled Follow-Up Appointment (4)
Panel A: Average effects				
Screening	0.03	0.02	-0.01	0.00
	(0.06)	(0.04)	(0.04)	(0.02)
Rewards	0.15**	0.09*	0.07*	0.03
	(0.07)	(0.05)	(0.04)	(0.02)
Rewards & Screening	0.09	0.11***	0.08**	0.01
	(0.06)	(0.04)	(0.04)	(0.02)
Controls	X	X	X	X
Control mean	0.19	0.03	0.03	0.01
Panel B: Heterogeneous effects				
Screening	0.05	-0.03	-0.03	-0.03
	(0.06)	(0.03)	(0.03)	(0.03)
Screening x Symptomatic	-0.06	0.13**	0.07	0.07*
	(0.11)	(0.06)	(0.06)	(0.04)
Rewards	0.22***	0.06	0.06	-0.03
	(0.08)	(0.05)	(0.05)	(0.03)
Rewards x Symptomatic	-0.15	0.05	0.03	0.09**
	(0.13)	(0.08)	(0.08)	(0.04)
Rewards & Screening	0.03	-0.03	-0.03	-0.03
	(0.06)	(0.03)	(0.03)	(0.03)
Rewards & Screening x Symptomatic	0.13	0.25***	0.19***	0.07*
	(0.11)	(0.08)	(0.07)	(0.04)
Control mean, Asymptomatic	0.05	0.03	0.03	0.03
Control mean, Symptomatic	0.30	0.04	0.04	0.00
Panel C: Hypotheses tests (p-values)				
Asymptomatic:				
Screening = Rewards	0.07	0.08	0.08	1.00
Screening = Rewards & Screening	0.72	.	1.00	1.00
Rewards = Rewards & Screening	0.03	0.08	0.08	1.00
Symptomatic:				
Screening = Rewards	0.43	0.93	0.47	0.62
Screening = Rewards & Screening	0.09	0.13	0.08	1.00
Rewards = Rewards & Screening	0.39	0.16	0.32	0.62
Observations	340	340	340	340

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table displays estimates of equations (1) (columns (1), (3), and (5)) and (2) (columns (2), (4), and (6)). The table also displays the baseline levels of the outcome variable in the control group, in total ("Control Mean"), and among individuals with ("Control Mean, Symptomatic") and without symptoms of depression and anxiety ("Control Mean, Asymptomatic").

Appendix Figure 1: Example of information provided to participants



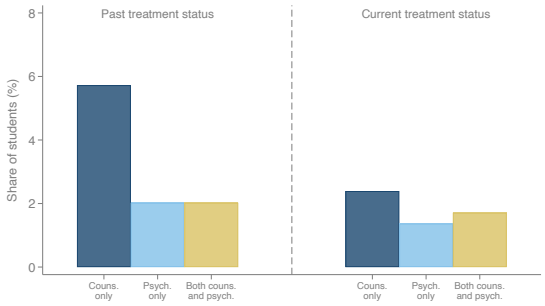
Your responses in the **"Mental Health Screening"** Section of this survey, indicate that **you currently may be experiencing a moderate degree of psychological distress.** You may benefit from speaking to a counselor.

You have also been randomly chosen to **receive a reward of Rs. 500 for attending your first therapy session** with a study counselor.

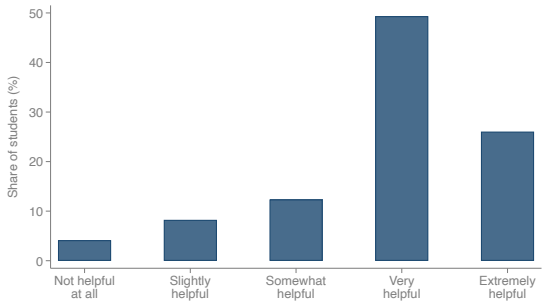
Notes: This figure displays an example of information shown to participants as part of the survey. The information on level of distress was shown to participants in the screening and screening and rewards arms. The information on rewards was shown to participants in the rewards and screening and rewards arms.

Appendix Figure 2: Mental health treatment history and perceptions at baseline

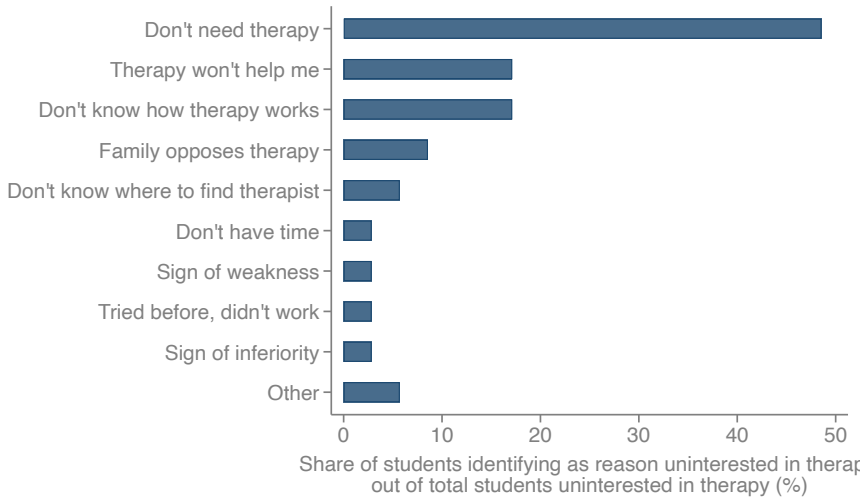
(a) Treatment history



(b) Perceived effectiveness of therapy

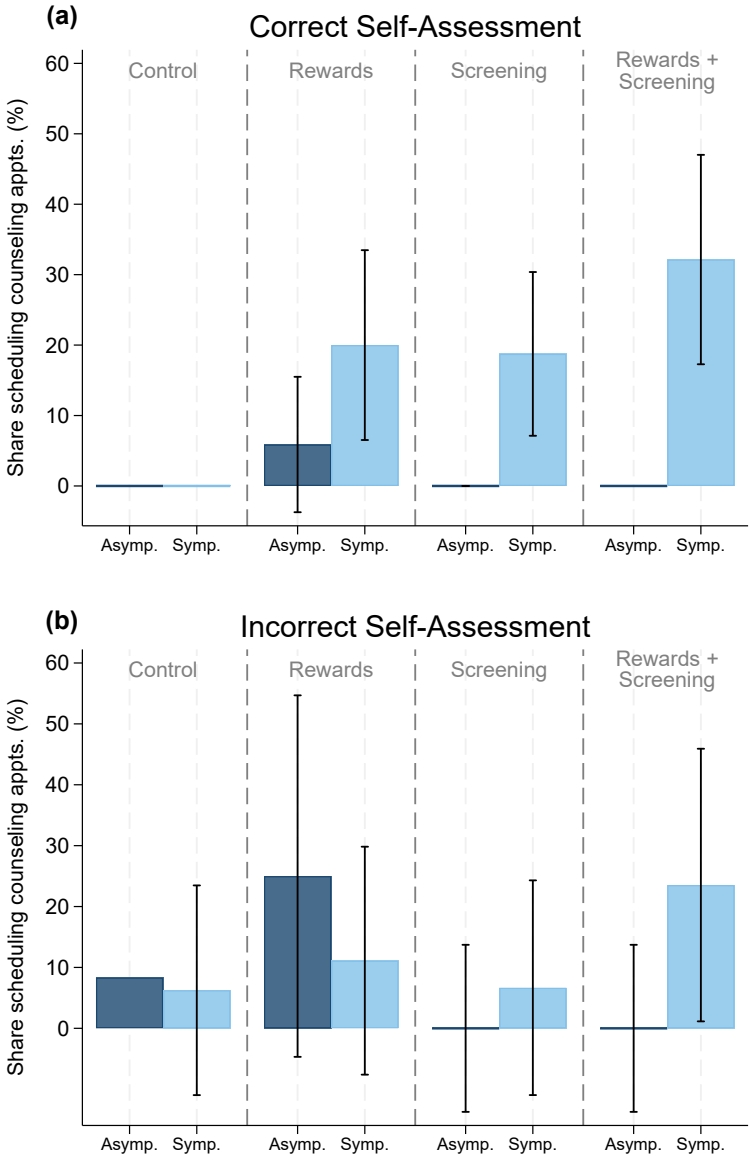


(c) Reasons not to take up therapy, among individuals in control group screening for depression or anxiety who do not contact counselors



Notes: This figure presents descriptive statistics on mental health treatment history and perceptions at baseline. Panel (a) shows the share of participants who have seen a counselor, a psychologist, or both a counselor and a psychologist, both in the past, and currently. Panel (b) shows participants' stated beliefs about the effectiveness of therapy. Panel (c) shows participants' stated reasons for not taking up therapy, among individuals in the control group who screen for depression or anxiety (PHQ-ADS score ≥ 10), but who choose not to initiate contact with counselors, either by messaging study counselors, or by requesting that they be contacted by study counselors.

Appendix Figure 3: Effects of treatment assignment on likelihood of scheduling counseling by correct or incorrect self-assessment of mental health status.



Notes: This figure shows the likelihood of scheduling counseling by baseline mental health status in each treatment arm. Panel (a) shows those who correctly assess their mental health status, and panel (b) those who incorrectly assess their mental health stauts. In panel (a), navy bars show the likelihood of scheduling counseling for asymptomatic individuals (PHQ-ADS ≤ 9) in each treatment arm, and light blue bars for symptomatic individuals (PHQ-ADS ≥ 10). Black bars show 90% confidence intervals relative to the control asymptomatic mean, computed using regression specification (2). For instance, the 90% confidence interval on the "screening, symptomatic" bar corresponds to the point estimate for α_0, plus the 90% confidence interval for the value of $\alpha_1 + \beta_0 + \beta_1$.

Appendix Table 1: Balance on Baseline Characteristics

	Control Mean (1)	Coef. on Screening (2)	Coef. on Rewards (3)	Coef. on Rewards & Screening (4)
A. Demographics				
Age	19.65	-0.21*	-0.01	-0.11
		(0.12)	(0.12)	(0.12)
Has Personal Disposable Income	0.45	0.10	0.12	0.16**
		(0.08)	(0.08)	(0.08)
Is Preparing for Competitve Exam	0.17	-0.03	0.05	0.08
		(0.06)	(0.06)	(0.06)
B. Mental Health (Self Perception)				
Good Mental Health (Current)	0.72	-0.02	-0.01	-0.02
		(0.07)	(0.07)	(0.07)
Good Mental Health (Past 2 Weeks)	0.23	-0.01	0.08	0.06
		(0.06)	(0.07)	(0.07)
Good Mental Health (Past 6 Months)	0.29	0.06	0.03	0.09
		(0.07)	(0.07)	(0.07)
Curently Has Depression or Anxiety	0.48	-0.03	-0.08	-0.04
(Self Reported)		(0.08)	(0.08)	(0.08)
Has Had Depression or Anxiety in the Past	0.65	-0.03	-0.13*	-0.10
(Self Reported)		(0.07)	(0.08)	(0.07)
C. Mental Health (Treatment)				
Currently Seeing Psychiatrist or Counselor	0.03	0.02	0.01	0.01
		(0.03)	(0.03)	(0.03)
Has Previously Seen Psychiatrist or Counselor	0.08	0.01	-0.01	0.01
		(0.04)	(0.04)	(0.04)
Family Support for Mental Health Treatment	0.28	0.03	0.01	0.04
		(0.07)	(0.07)	(0.07)
D. Mental Health (PHQ-ADS Scores)				
PHQ-ADS Score	12.40	0.76	-0.11	0.13
		(1.59)	(1.47)	(1.58)
Symptomatic: PHQ-ADS Score ≥ 10	0.55	0.01	0.01	0.02
		(0.08)	(0.08)	(0.08)
Mildly Symptomatic: PHQ-ADS Score 10 – 19	0.28	0.01	0.03	0.02
		(0.07)	(0.07)	(0.07)
Moderately Symptomatic: PHQ-ADS Score 20 – 29	0.22	-0.02	-0.03	-0.02
		(0.06)	(0.06)	(0.06)
Severely Symptomatic: PHQ-ADS Score ≥ 30	0.05	0.02	0.00	0.02
		(0.04)	(0.03)	(0.04)

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table displays levels of baseline variables in different treatment arms. Each row presents results for a baseline variable from an OLS regression of the form

$$B_i = \alpha + \beta \text{Screening}_i + \gamma \text{Rewards}_i + \delta \text{Screening and rewards}_i,$$

where B_i is the baseline variable. Column (1) shows the point estimate for α; columns (2), (3) and (4) show the point estimates and corresponding standard errors for β, γ, and δ, respectively. Panel A presents results for demographic baseline variables: participants' age; an indicator variable for whether the participant has personal income; and an indicator variable for whether the participant is preparing for a competitive exam or standardized test. Panel B presents results for self-perceived mental health: indicator variables for rating one's well-being currently, over the past two weeks, or over the past six months at least four out of five; and indicator variables for self-identifying as currently or previously having depression or anxiety. Panel C presents results for engagement with mental health treatments: indicator variables for currently or previously seeing a psychologist or counselor; and an indicator variable for family supporting engagement with mental health treatment. Panel D presents results for PHQ-ADS scores: a continuous variable for PHQ-ADS score; and indicator variables for the PHQ-ADS score indicating that a student is symptomatic, mildly symptomatic, moderately symptomatic, or severely symptomatic. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 2: Effects of pooled treatment assignment on primary outcomes

	Total interest in counselor contact (1)	Scheduled Appointment (2)	Attended Appointment (3)	Scheduled Follow-Up Appointment (4)
Panel A: Effects of pooled rewards				
Pooled Rewards	0.11**	0.09***	0.08***	0.02
	(0.05)	(0.03)	(0.03)	(0.02)
Controls	X	X	X	X
Control mean	0.20	0.06	0.04	0.02
Panel B: Effects of pooled screening				
Pooled Screening	-0.01	0.02	-0.00	-0.01
	(0.05)	(0.03)	(0.03)	(0.02)
Controls	X	X	X	X
Control mean	0.25	0.08	0.07	0.02
Observations	340	340	340	340

* $p < .10$, ** $p < .05$, *** $p < .01$

Appendix Table 3: Heterogeneous effects of pooled treatment assignment by baseline symptoms

	Total interest in counselor contact (1)	Scheduled Appointment (2)	Attended Appointment (3)	Scheduled Follow-Up Appointment (4)
Panel A: Effects of pooled rewards				
Pooled Rewards	0.10*	0.04	0.04	-0.02
	(0.06)	(0.03)	(0.03)	(0.01)
Pooled Rewards × Symptomatic	0.01	0.09	0.08	0.07*
	(0.09)	(0.06)	(0.06)	(0.03)
Controls	X	X	X	X
Control Mean, Asymptomatic	0.08	0.01	0.01	0.01
Control Mean, Symptomatic	0.29	0.09	0.06	0.02
Panel B: Effects of pooled screening				
Pooled Screening	-0.07	-0.06*	-0.06**	-0.02
	(0.06)	(0.03)	(0.03)	(0.01)
Pooled Screening × Symptomatic	0.09	0.15**	0.11*	0.02
	(0.09)	(0.06)	(0.05)	(0.03)
Controls	X	X	X	X
Control Mean, Asymptomatic	0.16	0.05	0.05	0.01
Control Mean, Symptomatic	0.33	0.10	0.09	0.03
Observations	340	340	340	340

* $p < .10$, ** $p < .05$, *** $p < .01$

Appendix Table 4: Heterogeneous effects of pooled treatment assignment by baseline degrees of distress

	Total interest in counselor contact (1)	Scheduled Appointment (2)	Attended Appointment (3)	Scheduled Follow-Up Appointment (4)
Panel A: Effects of pooled rewards				
Pooled Rewards	0.10*	0.04	0.04	-0.02
	(0.06)	(0.03)	(0.03)	(0.01)
Pooled Rewards × Mild	-0.02	0.04	0.03	0.03
	(0.11)	(0.07)	(0.07)	(0.04)
Pooled Rewards × Moderate-Severe	0.04	0.14	0.13	0.11*
	(0.13)	(0.09)	(0.08)	(0.05)
Controls	X	X	X	X
Control Mean, Asymptomatic	0.08	0.01	0.01	0.01
Control Mean, Mild	0.22	0.08	0.06	0.02
Control Mean, Moderate-Severe	0.37	0.11	0.07	0.02
Panel B: Effects of pooled screening				
Pooled Screening	-0.06	-0.06**	-0.06**	-0.02
	(0.06)	(0.03)	(0.03)	(0.01)
Pooled Screening × Mild	0.16	0.09	0.10	0.04
	(0.11)	(0.07)	(0.06)	(0.03)
Pooled Screening × Moderate-Severe	0.02	0.21**	0.12	-0.01
	(0.12)	(0.09)	(0.08)	(0.05)
Controls	X	X	X	X
Control Mean, Asymptomatic	0.16	0.05	0.05	0.01
Control Mean, Mild	0.22	0.08	0.06	0.00
Control Mean, Moderate-Severe	0.47	0.12	0.12	0.07
Observations	340	340	340	340

* $p < .10$, ** $p < .05$, *** $p < .01$

Appendix Table 5: Heterogeneous effects of pooled treatment assignment by baseline income

	Total interest in counselor contact (1)	Scheduled Appointment (2)	Attended Appointment (3)	Scheduled Follow-Up Appointment (4)
Panel A: Effects of pooled rewards				
Pooled Rewards	0.18**	0.00	0.03	-0.01
	(0.08)	(0.05)	(0.04)	(0.02)
Pooled Rewards × Has Income	-0.14	0.15**	0.10*	0.04
	(0.10)	(0.06)	(0.06)	(0.03)
Controls	X	X	X	X
Control Mean, No Income	0.19	0.08	0.06	0.02
Control Mean, Has Income	0.27	0.07	0.05	0.02
Panel B: Effects of pooled screening				
Pooled Screening	-0.03	0.01	-0.03	-0.01
	(0.07)	(0.05)	(0.05)	(0.02)
Pooled Screening × Has Income	0.03	0.02	0.04	0.00
	(0.10)	(0.07)	(0.06)	(0.03)
Controls	X	X	X	X
Control Mean, No Income	0.26	0.07	0.07	0.02
Control Mean, Has Income	0.29	0.15	0.12	0.06
Observations	340	340	340	340

* $p < .10$, ** $p < .05$, *** $p < .01$