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RESILIENCE-THINKING TRAINING FOR COLLEGE STUDENTS: EVIDENCE FROM A RANDOMIZED TRIAL[*]

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ABSTRACT: We conducted a randomized evaluation of a universal primary prevention intervention whose main goal was to increase the resilience of students from a large broad-access Hispanic Serving Institution and commuter urban college. In a 90-minute workshop, students were: introduced to the resilient-thinking approach, which offers conceptual tools to cope with unexpected negative shocks; worked individually and in groups to identify challenges in their community; and brainstormed strategies to address them. We find that the intervention increased by 5 percent of a standard deviation the short-run resilience of the average student. Importantly, the intention-to-treat effects were larger for students with lower levels of baseline resilience. The intervention was most effective among students with weaker individual protective factors at baseline (the most vulnerable students, those with lower resilience, and with higher mental health problems), and for those with stronger community protective factors, suggesting that individual and community factors mediate differently within this intervention. The intervention effects on students' resilience persisted over time. These effects were mostly driven by an improvement in students' collaboration (i.e., maintenance and formation of support networks and personal relationships), and vision (i.e., sense of purpose and belief in an ability to define, clarify, and achieve goals). We find no effects on educational performance the semester of the intervention or the following one, nor on depression and anxiety the following semester.

JEL Codes: I10, I18, I3
Keywords: Resilience, randomized control trial, mental health, low-touch interventions, higher education, protective factors.

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"I think of mental health as the fuel that allows us to show up for our communities, our friends, our family and our lives," Dr. Vivek Murthy, the surgeon general. The New York Times, March 21st, 2023

1. Introduction

On December 2021, the US Surgeon General warned that young people (15- to 24-year-olds) were facing "devastating" mental health effects because of the challenges experienced by their generation and that the COVID-19 pandemic had intensified such a rise in depression, anxiety and mental health distress among this group. Indeed, the OCDE (2021) reported that the mental health issues among this group have soared during the pandemic with young people being 30% to 80% more likely to report symptoms of depression or anxiety than adults in Belgium, France, and the US. There is also mounting evidence of the negative impact of the pandemic on the mental health of US college students with regards to stress, anxiety, and depression (Molock & Parchem 2021; Son *et al*. 2020). This mental health crisis is aggravated for individuals from lower income and/or ethnic minority backgrounds, including Blacks, Hispanics or Latinos, Asian Americans, and socioeconomically disadvantaged populations, as the pandemic exacerbated pre-existing social, economic, and health inequalities (Myers 2020; Essien & Venkataramani 2020).

This issue is of particular concern for minorities and low-income students enrolled in colleges not only because their success in higher education is a ticket to greater economic opportunities and upward mobility, but also because of the safety-net role many colleges play with housing, meal plans and jobs. Furthermore, an uneven return to in-person learning with many remote options for courses and services persisting, especially in public colleges, is aggravating the mental health crisis on campuses serving underrepresented populations. Empirical research on students from City University of New York (CUNY) institutions, the public university system in New York city serving more than one quarter of a million students each year, tells a devastating story. The COVID-19 pandemic was a sudden and unexpected shock that: (1) shattered many college students' financial and economic well-being with the effects being more severe for the most disadvantaged students—Pell recipients, first-generation students[1], and transfer students (Rodríguez-Planas 2022); and (2) led to major psychological distress with more exposure to pandemic-related stressors being associated with increased depression and anxiety (Rudenstine *et al*. 2021 and 2022). Protecting young people's mental

[1] First-generation college students are students who are the first in their family to attend college.

health, especially that of minorities and socioeconomically disadvantaged youths, both now and on a long-term basis, is one of society's greatest challenges and a top priority of the OECD, as called for by the OECD Recommendation on Integrated Mental Health, Skills, and Work Policy (OECD 2021).

In this paper, we present findings from a randomly designed universal primary prevention intervention whose main goal was to increase underserved college students' level of resilience, a well-known protective factor against exposure to adverse social determinants of health (Singer 2009; Göran & Whitehead 1991; Sachs et al 2020). The intervention took place in a large, urban, broad-access four-year college campus that is both a Hispanic-Serving Institution (HIS) and a commuter college. To the extent that Hispanic-Serving Institutions (HISs) enroll about one four of students attending colleges and universities in the US[2], and given that commuter students, that is those who do not live in institution-owned housing on campuses, make up more than 85 percent of today's college students (Kelchen 2018), our findings are salient for a significant number of students in higher education in the US today. This study represents, to our knowledge, the first experiment in higher education aimed at inducing a change in students' resilience through reflection of their community's challenges with a relatively low-intensity, low-cost universal primary prevention intervention that could easily be scaled up.

The randomly designed intervention consists of an in-depth group workshop where CUNY students were introduced to the resilient-thinking approach, a trans-disciplinary methodology borrowed straddling from ecology science (Folke 2016; Walker & Salt 2012) to mental health science (Theron *et al.* 2022; Ungar 2021; Cyrulnik 2021), that "offers conceptual tools to help us cope with the bewildering surprises and challenges of our new century" (Homer-Dixon 2010). This intervention is universal because it targeted the general undergraduate student population instead of a specific risk group within that population. The intervention is also a primary prevention intervention because its main objective was to increase students' level of resilience, a stress-resistance resource found to be important in promoting psychological well-being (Padmanabhanunni *et al.* 2023). While resilience has not been well-defined in the literature, with a discussion on whether it is a "trait", i.e., stable and enduring, or a "state", and hence, dynamic and malleable, we follow recent definitions of resilience that consider it a dynamic process

[2] In Fall 2021, about 19.0 million students attended colleges and universities (including non-degree-granting institutions) in the US (US Department of Education 2023). Of these, 4.6 million students were enrolled in a HISs (US Department of Education 2022).

through which the individual positively adapts to stressful events or adverse circumstances (Stainton *et al.* 2019). Following Fergus and Zimmerman's conceptualization of the resilience process (2005), the individual utilizes protective factors, such as individual assets and community resources, to cope with stressors and achieve positive outcomes.

After being taught key elements from the resilience-thinking approach, students worked both individually and in groups of five to seven students each, sharing their experiences about the challenges in their community both before and after the COVID-19 pandemic, identifying the most common challenges, brainstorming on strategies to address them, and identifying potential bottom-up solutions. Using an online survey, we measured students' resilience level with a clinically validated assessment tool—the 16-item Predictive 6 Factor Resilience Scale (PR6) from Rossouw & Rossouw (2016)—both at application and at the end of workshop, which were a month apart. At application, students' resilience level informs us on their individual protective assets at baseline. We also measured their community protective factors at application with students' self-reported measures of physical capital and social support in their neighborhood. Using clinically validated assessment tools, we further measured students' anxiety, depression, and post-traumatic syndrome (PTS) in the online survey and whether students were first-generation college students or born in the United States. Information on students' demographic characteristics and socio-economic status was extracted from QC administrative records. About six months after the workshop, we sent a follow-up survey to measure students' level of resilience, anxiety, depression, and post-traumatic syndrome (PTS) in the medium run. In Fall 2023, we obtained from QC academic records students' GPA both before and after the intervention.[3]

While many mental-health interventions, such as those meant to lower depression, are targeted towards individuals with more psychological need or risk (Breslau & Engel 2015), the current study invited a random sample of Queens College (QC) students to participate to the workshop. With over 15,000 students and located in one of New York City's outer boroughs, QC is one of twelve four-year colleges in CUNY. Its student population is ethnically diverse, primarily working-class, often balancing family and work responsibilities while pursuing a college degree. This frequently places QC among the top-ten ranked colleges in social mobility

[3] Academic records were not part of the original design, hence academic performance is not an outcome in the pre-registered trial. To compare our results to other low-touch interventions in higher education, we decided to collect and analyze the data ex-post.

in the US. Like universal interventions, the current intervention may have costs associated with wasted resources if there are little to no benefits for the healthy population. We conducted a battery of subgroup analyses using students' baseline socio-demographics, neighborhood social capital, and mental-health status to identify which groups benefitted the most and the least from the intervention to provide guidance for potentially scaling up the intervention.

We find that the resilience-thinking workshop increased by 5 percent of a standard deviation the short-run resilience of the average student, that is the student whose baseline resilience equals the average baseline resilience of the control group. Importantly, the intention-to-treat effects were larger for students with lower levels of baseline resilience. For students with baseline resilience at the bottom decile of the distribution (who had a resilience of 0.51), this intervention increased their resilience by 18 percent of a standard deviation, compared to 12 percent for those at the bottom quartile of the baseline resilience distribution. We also find that the intervention's impact on resilience persisted, yet we find no evidence that it impacted students' other mental-health outcomes in the medium run, between three to six months later. The intervention also did not have any academic impact the semester the intervention took place of the one that followed the intervention.

The short-term effect is stronger for Hispanics and Blacks, female students, transfer students, and juniors and seniors who had already begun college when the pandemic hit. We also find that the short-term effect is stronger and affects a larger share of students with signs of depression, anxiety, or post-traumatic stress (PTS) prior to the intervention. While the intervention proved most effective for students with lower levels of individual protective assets—those who are most vulnerable and at higher psychological risk—it was noteworthy that it also benefited students with stronger social capital. This suggests that the interaction between individual assets and community resources plays a vital role in helping individuals cope with stressors.

The short-term effect of the intervention is mostly driven by an improvement on students' maintenance and formation of support networks and personal relationships (collaboration), and sense of purpose and belief in an ability to define, clarify and achieve goals (vision). Since the short-term results were collected at the end of the workshop, the improvement could only have happened through collaboration with other workshop participants. Consistent with short-term findings, the intervention was most impactful in changing students' collaboration, vision, and also health. As it is unlikely that a 90-minute intervention prompted long-lasting friendships among the students that participated in the same workshop, and because the intervention empowered students to act within their communities, it is more plausible that the observed medium-term impacts are driven by students' improved relationships outside of the experiment.

Our study is related to studies experimentally testing light-touch (and low-cost) interventions targeted to the incoming or first-year college population.[4] A first group of light-touch interventions aim at improving the college application process or the renewal of financial aid by providing timely information or simplification of time-sensitive processes (Bettinger et al., 2012; Castleman and Page, 2015; 2016; Dynarski et al., 2018; Castleman and Sullivan, 2019; Page et al., 2019; Bergman et al., 2019; Gurantz et al., 2019; Bird et al., 2021).[5] A second group consists of light-touch online psychological interventions, known as growth mindset[6] and belonging uncertainty interventions[7], aiming at improving academic outcomes for under-represented incoming first-year students most frequently at selective private colleges or flagship universities (Aronson, Fried & Good 2002; Walton & Cohen 2007, 2011; Yeager *et al.* 2016; Broda *et al.* 2018).[8] A third set of (also) online interventions aim at improving study habits and academic outcomes of first-year economic-courses students by offering different intensities of virtual 'coaching' involving both information provision as well as personalized and sometimes continuous one-on-one assistance (Oreopoulos & Petronijevic 2023).[9]

In contrast to the above studies, our work shifts the attention to a low-touch in-person intervention aiming at improving students' resilience and mental health by offering a 90-minute

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[4] Other studies have experimentally tested comprehensive college-based support programs aiming at improving academic persistence and graduation rates among the college population (Scrivener et al., 2015; Sommo et al., 2018; Clotfelter et al., 2017). While finding beneficial results, these interventions are costly and difficult to scale up, in contrast with the low-touch ones described in the main text.

[5] While the earlier studies have found that these low-touch interventions were successful in improving college students' outcomes, such as completing a college application, filing for, or renewing financial aid, applying to selective colleges, or choosing courses on time; it is unclear whether such results generalize to larger populations and across different settings (Bergman et al., 2019; Gurantz et al., 2019; Bird et al., 2021).

[6] Growth mind set interventions aim at shifting the way in which students attribute academic success from stable factors (e.g., intelligence) to more unstable ones (e.g. effort or social conditions).

[7] Belonging interventions aim at reframing worries students may have about fitting in as normal, rather than as reinforcement of societal and institutional signals that they do not belong or are unable to succeed.

[8] Light-touch online psychological have found that the interventions helped underrepresented students become more socially and integrated and that they improved these students' academic outcomes (Aronson, Fried & Good 2002; Walton & Cohen 2007, 2011; Yeager *et al.* 2016; Broda *et al.* 2018). Focusing on students from a broad-based university, Murphy et al. (2020) also find that the light-touch sense-of-belonging intervention improved minority and first-generation first-year students' academic outcomes.

[9] Consistently, all these interventions have been found to improve study habits without impacting grades (Oreopoulos & Petronijevic, 2023).

in-depth group workshop that offers students conceptual tools to analyze and share their challenges within their communities and brainstorm solutions. Because the intervention is offered to a random sample of students at a broad-access commuter college (regardless of their class level), it broadens the focus of the intervention beyond incoming or first-year students. Because of rich baseline information, this intervention disentangles how aspects of students': (1) individual protective assets; (2) community protective assets; (3) socio-economic status; and (4) mental health may facilitate or foreclose the students' ability to benefit from the treatment allowing us to identify for whom this intervention may be most effective.

Our work also contributes to experimental psychological interventions aiming at reducing college students' stress through mindfulness training (Dvořáková *et al.* 2017); stress management in a self-help format (see Rose *et al.* 2013; Amanvermez 2020 and references within); and various psychoeducational interventions to enhance stress-related growth (Steinhardt and Dolbier 2008; Dolbier *et al.* 2010; Houston *et al.* 2017). While many of these interventions have shown modest beneficial effects on students' resilience, stress, depression, and anxiety, they often lack measurements of longer-term impacts. Additionally, their sample sizes are typically small, with the treatment group frequently comprising fewer than 50 students, which hinders the feasibility of conducting comprehensive heterogeneity analyses.

Our results are encouraging in that the intervention improved students' resilience both in the short and medium term. The intervention is most effective for students with weaker individual protective factors, characterized by lower resilience and/or higher mental health problems at baseline. Conversely, the intervention proves more effective for those with more reliable system protective factors, characterized by stronger social networks and/or greater resources in their neighborhoods. These results suggest that individual and system protective factors mediate differently within this intervention.

2. The Resilience-Thinking Workshops

Program Description. We randomly assigned eligible college students to participate in a 90-minute resilience-thinking workshop offered either in the Spring or Fall 2022 semesters at Queens College (QC). During the workshop, students were first introduced to the adaptive cycle model (Holling 1986), a useful tool to understand long-term dynamics of change for social systems as complex systems (Sundstrom & Allen 2019) as well as dynamics of community engagement and partnership building (Berinyuy *et al.* 2014). The resilience-thinking approach presents a frame of mind that allows individuals and communities to take a solving-problem approach in front of change such as stressors (low-burning such as unemployment), disruptions (collapse such as an eviction) and transformative changes (very long-term such as overcoming addictions). After the lesson on resilience thinking, students were asked to: (1) identify their community; (2) question themselves about their challenges within their community prior to the COVID-19 pandemic; (3) question themselves about the current systemic crisis; (4) analyze the current risks; (5) brainstorm about those risks; and (6) define how to initiate a sustainable "transition" process. Students first addressed these questions individually, and then shared them with their group. Through this process, students analyzed COVID-19-related challenges in their neighborhoods and identified visions on how to address them. By brainstorming on individual-, interpersonal-, and community-level challenges related to the pandemic, students internalized that they are part of a multilayer community, and that life is full of complexities.

All workshops were led by the same researcher with expertise applying the resilience-thinking approach to community participatory processes and facilitating community engagement in different communities, including low- and middle-income populations in New York City. In each workshop, there were an average of 13 to 14 students, who worked in gender- and race-balanced teams of five to seven students.

The workshops were well implemented with students engaging and participating in the different activities. All students were engaged and brainstormed within their subgroups. In addition, students presented in front of the whole group their main findings as documented in Figure 1. Figure A.1 in the Appendix displays a spider diagram showing the change in students' main perceived challenges before and after the pandemic collected during the workshops. While students underscored time management and academic issues as the most frequent perceived challenges pre-pandemic; loneliness, mental health, and, to a lesser extent, unemployment and family issues were more salient post-pandemic. Academic challenges persisted after the pandemic.

Application Process, Eligibility, and Randomization. One month before the workshops were to take place, a random sample of QC students were invited to apply online to participate in a resilience-thinking workshop after completing an online survey. Students were informed that, due to space limitations, application was no guarantee of being selected to participate in the workshop as only a small group of students would be selected by lottery; and that workshop participants would be remunerated $50 cash at the end of the workshop and after completion of the exit survey.

To be eligible to participate, students had to be 18 years old or older, registered to classes during the semester of the workshop, seeking an undergraduate degree, and had to apply online to participate in the 90-minute workshop. Most survey respondents (92.8% in Spring and 95% in Fall) applied to the workshop, adding to a total of 750 applicants, 335 of which did so in the Spring semester. Due to budget constraints, the evaluation sample was limited to 76 students in the Spring semester, and 186 students in the Fall semester. Hence, a total of 260 students were randomly assigned to the treatment group. As we randomly selected a similar number of students from the pool of applicants to the control group, our sample size amounted to 521 students.

Students assigned to the treatment group were informed on the location, time, and date of the workshops within two weeks of application and about two weeks prior to the day of the workshop. Students in the control group were told that they did not get selected, and that more workshops would be offered in the future. In Spring 2022, four workshops were conducted over two days (two workshops per day, a week apart from each other). In Fall 2022, six workshops were conducted over two consecutive days (three workshops per day). Workshops were offered in the morning, afternoon, and during the lunch break to accommodate students' schedules. Students in the treatment group were assigned to a workshop based on their preferred time. All workshops took place in an ample conference room at the QC library. In general, students did not know each other as QC student population is over 15,000 students. Faculty and staff involved in the evaluation also did not know the students.

3. Data and Descriptive Statistics

The data for this study come from: (1) baseline information collected prior to random assignment via the application survey; (2) program implementation participation data; (3) QC administrative data; (4) an exit survey conducted at the end of the workshop, (5) a follow-up survey conducted about 6 months after random assignment; and (6) QC students' academic records.

Application Survey. In the application survey, students were asked to: (1) give consent to participate in the workshop, access their administrative and academic records, and contact them again in a follow-up survey; (2) enter their contact information and CUNY student ID; and (3) respond to questions regarding their resilience, mental health, US-born status and first-in-their-family-to-attend-college (first-generation) status, as well as questions regarding their neighborhood's physical capital and their social engagement in their neighborhood.

We measure resilience and mental health with clinically validated assessment tools. Students' resilience level was measured with the 16-item Predictive 6 Factor Resilience Scale (PR6), which incorporates health and six domains of psychological resilience: vision, composure, momentum, tenacity, reasoning, and collaboration. PR6 asks individuals how well the following statement define them as a person, with questions such as *"I have clear goals that I am working towards"* or *"I struggle to stay motivated"* where the student chooses to respond with a scale 1 to 5 where 1 is *"not at all like me"* and 5 is *"very much like me"*. The six domains are described in Rossouew (2016). Vision is a measure of sense of purpose and clarity of personal goals. Composure is a measure of ability to manage stress and regulation of emotional impulses. Reasoning is a measure of the ability to solve problems, be resourceful, and anticipate and plan for future adversity. Tenacity is a measure of the ability to maintain persistence, motivation and bounce back from adversity. Collaboration refers to the maintenance and formation of support networks and personal relationships. Momentum is a measure of attitudes toward future opportunities, appraisal of new challenges, problem-solving approach, as well as avoidance attitudes such as procrastination tendencies (Rossouw et al. 2017). Health refers to physiological health, including good nutrition, quality sleep and regular exercise.

Average scores are calculated within each domain, and the overall average score across all domains is used to determine each student's overall resilience. If a student did not respond to one of the questions, the average score within that domain for such student is calculated across the responses in that domain for which we have information.[10] We conduct a robustness check using only students who responded to *all* the questions in the results section. The PR6 is a

[10] This works since most students who had non-responses for a resilience question in the application survey had only one non-response. All 24 students in the treatment group with non-responses had either one non-response or two non-responses but in different domains. The same is true for 18 of the 20 students in the control group with non-responses. The other two students in the control group had entire domains missing. For these two students, we estimated the average score using the domains where they responded. Results are robust to excluding these two students from the analysis, instead.

psychological resilience measurement tool with a focus on the psychological aspects of resilience. The PR6 has internal consistency score of 0.8398, with each domain separately validated (Rossouw & Rossouw 2016).[11]

To measure depression, we used the nine-item Patient Health Questionnaire-9 (PHQ-9), which asks individuals whether they have been bothered by different symptoms over the past two weeks as shown in Appendix Table A.1. Each of the 9 items is rated on a 4-point scale ranging from 0 (*not at all*) to 3 (*nearly every day*). We categorize depression severity by total scores of 0–4 for no depression, 5–9 for mild, 10–14 for moderate, and 15 or higher for severe depression. These cutoff scores are well established in the literature documenting the association between PHQ-9 scores and ratios of depression diagnoses. The PHQ-9 has demonstrated internal reliability, with previous analyses documenting a Cronbach's alpha value of 0.89 and a test–retest reliability correlation of 0.84. It also has demonstrated a sensitivity of 88.0% for scores of 10 and higher (Kroenke *et al.* 2001).

To measure anxiety, we used the seven-item Generalized Anxiety Disorder-7 (GAD-7), which asks individuals whether they have been bothered by different problems over the last two weeks as shown in Appendix Table A.2. Respondents rate the seven items using a 4-point scale ranging from 0 (*not at all*) to 3 (*nearly every day*). We define anxiety severity as follows: total scores of 0–4 for no anxiety, 5–9 for mild, 10–14 for moderate, and 15 or higher for severe anxiety, in accordance with the literature. The GAD-7 has strong internal reliability (Cronbach's $\alpha = .92$) as well as a test–retest correlation of 0.83. It has demonstrated a sensitivity of 89.0% for a cutoff score of 10 (Spitzer *et al.* 2006).

In addition to measuring psychological resilience, depression, and anxiety, we also measure students' post-traumatic stress with the PCL-5, a 20-item self-reported measure that assesses the 20 DSM-5 symptoms of post-traumatic stress (PTS) disorder. The PCL-5 asks individuals whether they have been bothered with a list of problems in the last month, as shown in Appendix Table A.3 (Weathers *et al.* 2013). Respondents rate each item from 0 ("*not at all*") to 4 ("*extremely*") to indicate the degree to which they have been bothered by that symptom over the two weeks. We define PTS severity using the DSM-5 diagnostic rule, which is based on whether a student rates enough of certain items a 2 or higher (see top of Appendix Table A.3 for full

[11] Because of proprietary reasons, we are not allowed to disclose the questions in the PR6 questionnaire. For more information on how to access such questionnaire, see https://home.hellodriven.com/research/pr6-model/ .

definition). The PCL-5 test scores have demonstrated strong internal consistency ($\alpha = 0.94$ to 0.96), test-retest reliability ranging between 0.74 to 0.85, and convergent and discriminant validity (Blevins *et al.* 2015; Bovin *et al.* 2016).

Finally, we compiled two measures of neighborhood-of-residence social capital (physical order and social support) from survey questions shown in Appendix Table A.4. The physical order measure is based on statements about the physical capital of the neighborhood such as “There are trees along the streets”. The social support measure is based on the students' and their neighbors' involvement in group activities and community support. Social support questions which came from the Southeastern Pennsylvania Household Health Survey (SPHHS) 2018–2019 (Ransome et al. 2021).

Administrative Data. We have three types of administrative data: program implementation and participation data; socio-demographic characteristics of students collected by the college when the student first enrolled at QC; and academic records. Program implementation data informs us on which students were randomly assigned to the treatment and control group, which workshop students in the treatment group were assigned to, and whether they attended the workshop. QC administrative records describe students’ socio-demographic characteristics such as sex, age, race and ethnicity, class level, Pell-grant receipt, transfer-student status, and part-time student status. QC academic records contain students’ semester GPA measured the semesters before, during, and after the intervention.

Baseline Characteristics. Table 1 reports means and differences in means by treatment status for our baseline variables measured before randomization (hereafter baseline variables). Our sample is racially diverse with high shares of Hispanics, Asians, and Blacks. The sample also has high shares of female students, Pell recipients, and transfer students. While our sample is representative of the QC undergraduate population in terms of race/ethnicity and US born, it has a higher share of women, students younger than 23 years old, lower class-level students, and part-time students than that of QC population as shown in column 5.[12] Our sample also has a higher share of vulnerable students, defined as Pell recipient, transfer students, or first-

[12] Column 5 shows QC population means, when available. If such information is not available, we show means from either a QC-student sample or a CUNY-student sample collected at the end of summer 2020 or in spring 2020 by Rodríguez-Planas (2022) and Rudenstine *et al.* (2022), respectively.

generation students. Moving to the students' community resources, they had slightly positive views for physical order (M = 1.92 on 0-3 scale), and slightly negative views for social support (M = 1 on 0-3 scale).

Comparing QC to other colleges and universities, we can say that undergraduate enrollment is more diverse at QC. In particular, the Hispanic population is high with QC being officially designated a Hispanic Serving Institution (HSI) which require at least 25 percent Hispanic student enrollment. HSIs, which in the 2019-20 school year made up 17 percent of all institutions of higher education and enrolled about one four of students attending colleges and universities in the US (US Department of Education 2022, 2023), have a diverse set of students overall, with 67 percent of all Hispanic undergraduates, 41 percent of all Asian American, and 24 percent of all Black undergraduates attending one (HACU 2021). Compared with other HSIs, QC has lower share of Hispanics and whites and a higher share of Asians as seen by comparing QC means with those in column 6 of Table 1.[13]

Figure 2 shows the density of the distribution in resilience at baseline by treatment status. Measured at baseline, resilience is a proxy for individuals' protective factors. We observe that there is significant variation among both treatment- and control-group students with each group having a 0.126 standard deviation. While the distribution for the control group is slightly skewed left with a mean of 0.662 (less than the median of 0.679), the treatment group has both a mean and a median of 0.671 for resilience. Given the very similar distributions, the median for the control group nearly divides the treatment group in half with 51 percent of students in the treatment group having baseline resilience below the median for the control group. The QC overall distribution is close to the distribution of resilience for healthcare, education, and financial service professionals in Australia and New Zealand, which has a mean of 0.688 and standard deviation of 0.117 (Rossouw & Rossouw 2016).

Focusing on the other mental health variables, about two fifths of our sample have moderate to severe depression, about one third have moderate to severe anxiety, and 28 percent have PTS disorder. As a comparison, using different samples of college students interviewed pre-pandemic, authors have estimated that 14 percent of college students have moderate depression or higher (Eisenberg *et al.* 2007)[14], 24 percent have moderate to severe anxiety (Byrd-

[13] QC is located in Flushing, Queens, a predominantly an Asian community with Asians representing over 69 percent of its population.

[14] Based on a sample of 1,181 undergraduate students from a Midwestern US university survey in 2005.

Bredbenner, Eck & Quick, 2021)[15], and 26 percent have PTS disorder (Ashbaugh *et al.* 2016)[16]. While our sample averages higher levels of depression and anxiety than the average US college student, the differences in PTS disorder are minimal. Importantly, when we can compare our sample to a sample from the broader set of students at CUNY taken in Spring 2020 (shown in the column 5 in Table 1), the rates of depression, anxiety, and PTS are similar suggesting a possible persistence in these mental health issues after the onset of COVID-19 or, if those rates declined in CUNY overall, a higher rate of these mental health issues at QC.

Balance Tests. Randomization was well done. The balance tests, shown in Column 3 in Table 1, reveal that random assignment to treatment led to a balanced panel of treatment vs. control with only one statistically significant difference, anxiety, with students with moderate to extreme anxiety more likely to be assigned to the control group. These balance tests reveal that only one of 20 coefficients is statistically significantly different from zero at the 1% level, which is a chance of 5 percent. We will show that our results are robust to controlling for students' baseline characteristics, including anxiety before randomization.

Post-Intervention Surveys. Two additional surveys were conducted after the workshop. The exit survey is a short questionnaire with only the 16-item Predictive 6 Factor Resilience Scale (PR6) that workshop participants responded to. It is used to measure our main outcome: short-term resilience. In addition, about six months after the workshop, we distributed to the broader set of students who expressed interest in participating in the workshop, regardless of whether they were invited to participate or were assigned to the treatment or control groups, a follow-up survey. This follow-up survey was a longer than the exit survey as, in addition to the items for PR6 scale, it contained items for the PHQ-9 and GAD-7 scales for depression and anxiety, and the 5 items for the PCPTSD-5 scale, as a shorter alternative to the 20-item PC-5 scale for PTS.[17]

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[15] Authors' estimates based on results from a sample of 4,128 students from a US university over the 2009-2019 period; 16% of males (n=1,601) and 29% of females (n=2,527) reported were above the GAD screening-cutoff point of 10.

[16] Based on a sample of undergraduate students recruited from the University of Ottawa (n = 1184) and McGill University (n = 249) in Canada, the authors find that "signal-detection analysis revealed that a PCL-5 cut-off score of 31 best predicted this PTSD diagnostic grouping based on the DSM-5, yielding a prevalence of 26.3% with a specificity of .95, sensitivity of .85, and an efficiency of .95."

[17] If a respondent denies exposure, the PC-PTSD-5 is complete with a score of 0. However, if a respondent indicates that they have had any lifetime exposure to trauma, the respondent is instructed to respond to 5 additional yes/no

Outcomes. Our short-term outcome is the student's level of resilience measured after the workshop (about two weeks after randomization and one month after application) with the PR6 scale. For students in the treatment group who did not participate in the workshop as well as for control-group students, we use their resilience level at application instead. Our medium-term outcomes include resilience, anxiety, depression, and PTS all measured in the follow-up survey, about six months after randomization. In addition, we also estimate the impact of the intervention on semester GPA for the semester the intervention took place and the semester that followed.

Outcomes' response rates at application and exit survey were high. For the full set of questions for resilience, depression, anxiety, and PTS, the response rates for the treatment group are 90.8, 95.8, 95.0, and 92.7 percent while for the control group, they are 92.3, 92.3, 92.7, and 89.7 percent. As explained above for the students with non-responses to items in the resilience questions, we were able to use information from their responses to the other resilience questions to create a resilience index for 100 percent of the treated- and control-group students. As expected, the response rates for the follow-up survey are considerably lower (33.4 percent for students in the treatment group and 19.5 percent for those in the control group). Same semester GPA response rates are 92.3% and 97.7% for treatment- and control-group students. The following semester GPA response rates are 90.0% and 93.4% for treatment- and control-group students. [18]

In the robustness section, we provide evidence that it is unlikely that our short-term findings are driven by the fact that treated students have responded to the resilience questionnaire two consecutive times by showing that non-treated students who responded to both the baseline and follow-up surveys, and hence also responded the resilience questionnaire two consecutive times, do *not* experience an increase in their resilience level, but a non-statistically significance decrease. This suggests that any positive effect of the intervention on students' resilience may be an underestimate of the effect.

questions about how that trauma exposure has affected them over the past month. The scale has a documented cutoff score of 3, a sensitivity of 91%, and has a strong test–retest reliability of 0.83 (Prins *et al.*, 2003).

[18] The response rates for the previous semester GPA are 66.2% 70.7% for treated- and control-group students as some of our students are freshmen.

Workshop Participation. Since only about half of the students selected into treatment attended the workshops (42 of 76 treatment students in Spring 2022, and 94 of 186 treatment students in Fall 2022)[19], it is plausible that attendees differed from non-attendees in different dimensions. To explore this, Table 2 shows results from a logit regression where the dependent variable is a dummy equal 1 if the student participated in the workshop and 0 if she did not and the covariates are a spring semester dummy and basic controls (all demographic variables except born in U.S.A. and first-generation due to item non-responses), using only the students in the treatment group sample. The second column has a full set of controls, which adds U.S.A. and first-generation dummies, as well as dummies for moderate to severe depression, anxiety, and PTS to the basic controls. The only statistically significant coefficient is the one for Black, with Black students more likely to attend the workshop than white students. In our results section, we present estimates for the treatment effect of the workshop that control for a basic set of controls, including race. Furthermore, we will present heterogeneity analysis by race.

4. Evaluation Framework

We report intention-to-treat (ITT) estimates, making no adjustments for whether students in the treatment group attended the workshop or not. They are estimated from the following equation:

$$Y_{is} = \alpha_0 + \beta_1 Treatment_{is} + \beta_2 Resilience_{is}^{pre} + \beta_3 (Treatment_{is} * Resilience_{is}^{pre}) + \beta_4 X_{is}^{pre} + \delta_s + \epsilon_{is}$$

where Y_{is} is the outcome of student *i* who applied to the workshop in semester *s*. $Treatment_{is}$ is a dummy variable that takes value 1 if the student belonged to the treatment group, and 0 if she belonged to the control group. $Resilience^{pre}_{is}$ measures the level of resilience before randomization of student *i* who applied to the workshop in semester *s*, it informs us on students' individual protective assets at baseline. Because the intervention is offered to all students instead of to a specific at-risk group, we have students with rather high resilience levels as well as rather low. Controlling for baseline resilience allows us to discuss the change in resilience after the intervention rather than just the final level of resilience. It also allows us to estimate the

[19] Low use of services offered to students in the treatment group in not unusual among the college population. For example, in Angrist *et al.* (2009), between 26% and 43% of students in the treatment group offered peer-advising and/or supplemental instruction services ended up using those services.

intervention's differential impact based on students' baseline resilience. X_{is}^{pre} is a vector of students' baseline characteristics that varies with the specification; δ_s is a semester dummy equal 1 if the student applied to the workshop in Spring 2022, and 0 if she applied to the workshop in Fall 2022. This specification assesses whether the resilience-thinking workshop changed students' resilience based on their prior resilience by also including the interaction between treatment and baseline resilience. This allows the treatment effect to vary across the distribution of baseline resilience in both size and direction.

Since randomization was done at the semester level, we did not cluster the standard error at the unit of randomization. We present three sets of estimates: without controlling for students' baseline characteristics, and with two sets of controls, a basic one and a full one. The preferred specification has the basic set which controls for sex, age, race and ethnicity, class standing, Pell-status, transfer status, and whether the student is a part-time student. The full specification adds mental-health variables to the basic set of controls.

Students' baseline and short-term outcome resilience levels are normalized by subtracting the control group's average resilience at baseline and dividing by the control group's standard deviation also at baseline. Hence, for students whose baseline resilience is equal to the control group's average baseline resilience level (that is whose $Resilience_{is}^{pre} = 0$), a positive β_1 means that the workshop increased the student's resilience by β_1 standard deviations. Importantly, a negative β_3 does *not* necessarily mean that the workshop decreased the student's resilience. In fact, for students whose baseline resilience is *below* the control group's baseline mean—and hence $Resilience_{is}^{pre} < 0$, a negative β_3 means that the workshop increased the student's resilience level by $(\beta_1 + \beta_3 * Resilience_{is}^{pre})$ standard deviations. In addition to showing ITT estimates, we plot the ITT effects of the resilience-thinking workshop using the treated group's baseline resilience density to portray how the workshop's impact on students' resilience varies with their baseline resilience level. By construction, β_2 is close to 1.

5. Main Findings

Table 3 shows our main results with the first two columns showing the ITT estimates with and without the basic controls. Column 2, which presents estimates controlling for socio-demographic covariates measured at baseline is our preferred specification. The ITT estimate of 0.05 for β_1 in column 2 indicates that the resilience-thinking workshop increased by 5 percent of a standard deviation the resilience of students whose baseline resilience equals the average baseline resilience of the control group. As $\beta_3 = -0.111$, the workshop increased resilience by 16.1 percent of a standard deviation for students with baseline resilience one standard deviation *below* the control group's mean ($\beta_1 + \beta_3 = 0.05 + 0.111 = 0.161$). Yet, for students with baseline resilience one standard deviation *above* the control group's mean, attending the workshop decreased their resilience by 6.1 percent of a standard deviation ($\beta_1 + \beta_3 = 0.05 - 0.111 = 0.061$). β_1 is statistically significant at the 10 percent level, and β_3 is statistically significant at the 1 percent level.

To show the ITT effects across the whole set of students in the treatment group, Figure 3 plots the densities for the estimated treatment effects using three different specifications: one with no controls, one with basic controls, and one with full controls (shown in columns 1, 2, and 5 in Table 3). The figure shows that the workshop increased students' resilience in the treatment group for students in the bottom three-fifths of the baseline resilience distribution. Yet, when we estimate joint significance tests on $\beta_1$and β_3 for different levels of pre-resilience, the treatment effect is positive and statistically significant at the 10% level or better for students in the treatment group whose baseline resilience lies below the mean of the distribution, that is those with treatment impact above the solid vertical line in Figure 3.

Importantly, the ITT effects are larger for students with lower levels of baseline resilience. For example, for students with baseline resilience at the bottom decile of the baseline distribution (who had a resilience of 0.51), this intervention increases their resilience by 18 percent of a standard deviation, compared to 12 percent for those at the bottom quartile of the baseline resilience distribution, and only 5 percent of a standard deviation for those at the average of the baseline resilience distribution. [20]

For students with baseline resilience levels 0.441 or more standard deviations above the control group's mean ($\frac{-\beta_1}{\beta_3} = \frac{-0.049}{+0.111} = 0.441$), the ITT effect that includes basic controls becomes negative. Yet, when we estimate joint significance tests on $\beta_1$and β_3 for different levels of pre-resilience, the treatment effect is negative and statistically significant at the 10% level *only* starting for students with pre-resilience at 0.93 standard deviations above the mean for the control group, which represents 21% of the resilience baseline distribution. To put it differently,

[20] Treatment effect comes from plugging in the baseline resilience of the student at the relevant percentile for baseline resilience for the treatment group into the formula $\beta_1 + \beta_3 * Resilience_{is}^{pre}$.

the workshop decreases the resilience of students in the top fifth of the treatment group's baseline resilience distribution. While this intervention decreases resilience for students at the top of the baseline resilience distribution, the size of the negative effects is considerably smaller than the size of the positive effects. For example, for those in the top quartile of the baseline distribution, this intervention decreases their resilience, but by only a non-statistically significant 3 percent of a standard deviation, and for those in the top decile of the baseline distribution, it decreases their baseline resilience by 10 percent of a standard deviation. However, as students in the top decile of the baseline resilience distribution had very high levels of resilience (namely 0.83), the intervention only shifts their resilience from 0.83 to 0.82. For psychological treatments in general, there is the possibility that an intervention will have positive effects for some individuals and on average, but have negative effects on others (Barlow 2010).

In summary, students in the bottom half of the baseline resilience distribution benefitted from the resilience-thinking workshop whereas those in the top fifth of the baseline distribution experienced a decrease in their baseline resilience. The rest did not experience any change in resilience at the end of the workshop. It is also noteworthy that the intensity of the impact was inversely related to students' baseline resilience.

Robustness Checks. Columns 3 to 6 in Table 3 show that our estimates of β_1 and β_3 are robust to various sensitivity analyses, such as replacing the semester dummy with workshop fixed effects (column 3), adding baseline controls for moderate to severe depression and anxiety, or PTS disorder (column 5), or using only respondents to all PR6 questions—as opposed to calculating an average score within domains for non-responses (column 6). As there is some item attrition for baseline mental health variables, column 4 shows the specification with basic controls using the sample of students who responded to all baseline mental health questions. The similarity between estimates in columns 2 and 4 suggests that item attrition is not a concern. Moving from columns 4 to 5 suggests that the imbalance observed between treatment and control students in baseline anxiety is not affecting our ITT estimates. Comparing columns 5 and 6 suggest that domain-attrition for the PR6 questionnaire reduces our estimates and precision a tad, yet the main findings hold. Figure 3 also shows that our results are robust to adding different sets of covariates in the specification. This is particularly true for the share of students who benefitted from the intervention, which is always those in the bottom half of the baseline resilience distribution, regardless of specification. In contrast, the share of students whose resilience level decreased after the intervention narrows from those in the top quartile (24.4 percent) of the resilience baseline distribution to those in the top fifth (18.7 percent) of the baseline distribution as we add covariates in the specification.

Concerns that our results are driven by the fact that treated students have seen the resilience questionnaire twice, whereas the control only once, are addressed in Appendix Table A.5. Since we have follow-up responses for resilience for students in the control group and students who were neither assigned to the treatment or control group, we regress students' resilience measured at baseline and in the follow-up survey on a dummy equal 1 if the variable was measured in the follow-up survey and 0 if it was measured at baseline using *only* follow-up survey respondents in the control group or who were not in the experimental group. Evidence of an improvement in resilience in the follow-up survey would be indicative that our findings may be an artifact of responding to the resilience questionnaire a second time. The coefficients on the follow-up dummy in columns 1 and 2 in Table A.5 are negative and not statistically significant, regardless of whether we use an individual fixed effects model (column 1) or pooled OLS model with the basic set of demographic controls (column 2). Importantly, because the coefficient is negative, it reinforces that our findings are not due to just resilience scores rising at the end of the workshop regardless of treatment status.

6. Subgroup Analysis

Heterogeneity analysis is conducted by re-estimating the specification with basic controls (column 2 in Table 3) separately for different subgroups. Figures 4-7 show the densities for the ITT effects for the different subgroups, and Tables 4 and 5 show the ITT effect at the bottom and top quartiles for each subgroup. Figure 4 shows demographic differences such as sex, race/ethnicity, and US-born status. Figure 5 shows differences by whether the student is vulnerable or not, defined as Pell recipient, first-generation student, or transfer student status. The bottom of Figure 5 also shows heterogeneity by students' class level as freshmen and sophomores were still in high school when the pandemic hit, whereas juniors and seniors had already started college. Figure 6 shows heterogeneity based on students' neighborhood-of-residence social capital. Figure 7 shows heterogeneity analysis by students' baseline risk of anxiety, depression, or PTS disorder.

Socio-Demographic Characteristics. Figure 4 shows that the resilience-thinking workshop was more effective for black and Hispanic students, students born in the US, and female students than for white and Asian students, non-US born students, and male students. For example, the ITT was positive and significant for: (1) Black and Hispanic students whose baseline resilience was in the bottom three fifths (59 percent) of the treatment baseline resilience distribution—versus students from other races whose resilience was in the bottom fifth (19 percent) of the baseline distribution; (2) US-born students in the bottom half (53 percent) of the baseline resilience distribution—versus non-US born students in the bottom quarter (26 percent) of the baseline distribution); and (3) women in the bottom half of the baseline resilience distribution (47 percent)—versus no effect for men.

In addition to impacting a larger share of students, the ITT was considerably larger for Blacks and Hispanics, as well as for women than for other races, and males. Table 4 shows that the ITT effects for Blacks and Hispanics or women at the bottom quartile of the baseline resilience distribution were about three times larger than the effects for whites and Asians or males at the bottom quartile of the baseline distribution: 19 and 15 percent of a standard deviation versus 6 and 5 percent—yet these latter ITT estimates were not statistically significantly different from zero.

Income and Class-Level. Figure 5 shows that the resilience-thinking workshop was particularly effective among transfer and first-generation students with those in the bottom half of the baseline resilience distribution experiencing a boost in their resilience after the workshop. In comparison, the workshop was effective only for students who began QC as freshmen and whose baseline resilience was in the bottom quartile of the distribution, and for students whose parents had attended college and who were in the bottom tier of the baseline resilience distribution. A higher share of Pell recipients benefitted from the workshop (those in the bottom two fifth of the baseline distribution) than their peers who did not receive Pell grants (those in the bottom fifth of the distribution) though the estimated size of the effect for those in the bottom quartile of the distribution is similar regardless of Pell status (albeit not statistically significant for non-Pell recipients) as shown in Table 4.

The workshop benefited upper-class level students in the bottom half of the baseline resilience distribution, but only lower-class level students in the bottom 6 percent of the baseline distribution. The ITT effect for those in the bottom quartile of the resilience distribution was twice as large and statistically significant for upperclassmen than lowerclassmen. These results suggest that the intervention may be more useful for those who were hit by the pandemic while they were starting college.[21]

Community Protective Factors. As the process of resilience also entails the individual utilizing community resources to cope with stressors and achieve positive outcomes, we expect that an intervention that boosts coping mechanisms would be most effective among those who already have higher community resources (such as social support or physical capital in their neighborhood). Using students' responses, we constructed a dummy indicating whether the student was above the control group's median in perceived physical capital or social support or not. Figure 6 shows that the intervention was effective for a higher share of students reporting high physical order or social support in their neighborhood than for those reporting low levels of neighborhood physical order and social support—about half of the baseline distribution for those with strong community resources, but only a tier (physical order) or decile (social order) of the baseline distribution for those lacking such resources. Table 5 reveals that in addition to boosting the resilience of a higher share of students with strong community resources, the intervention had a higher impact on them than on those with weaker resources. Among students in the bottom quartile of the baseline resilience distribution, the ITT is 14 and 24 percent of a standard deviation for those reporting high physical order and social support versus 9 and 7 percent for those reporting low physical order and social support (albeit the latter of these coefficients is not statistically significant).

Psychological Risks. Figure 7 shows that the workshop was more likely to have a more beneficial effect for students classified as likely to have a mental health issue. Students with PTS disorder laying in the bottom two-thirds of the baseline resilience distribution and those with moderate to severe depression at baseline laying on the bottom 70 percentile of the baseline

[21] Redoing the subgroup analysis by whether the student is 20 years old or older versus younger than 20 years old delivers a similar result as the analysis by class level.

resilience distribution experienced a boost in their resilience level after attending the workshop relative to students with no PTS disorder symptoms in the bottom quartile and none of those with no depression symptoms. A higher share of students with moderate to severe anxiety at baseline benefited from the workshop than those with no anxiety (bottom 54 percentile versus bottom 28 percentile). In addition to the workshop impacting a higher share of students with mental health issues, the boost in resilience was larger for them at baseline as seen in Table 5 with the effect being 4 times larger for students with moderate to severe depression (17 versus 4 percent of a standard deviation) and more than double for students with likely PTS (18 versus 7 percent of a standard deviation).

7. **Type of Resilience**

Analysis of which resilience domains improved the most is done by re-estimating the specification with basic controls separately for each domain score (results shown in Appendix A.7). Figure 8 shows the densities for the ITT effects for each domain, and Appendix Table A.6. displays the estimates.

Figure 8 shows that out of the 7 domains, the intervention improved health and reasoning for students in the bottom quartile of the baseline distribution; composure, momentum, and tenacity for those in the bottom tier or two fifths of the baseline distribution; and collaboration and vision for those in the bottom half of the baseline distribution. The focus of the workshops with students spending quite some time working with other students, reflecting about their lives and those of others and how to overcome their challenges is consistent with a stronger impact in domains such as vision and collaboration. Since the short-term results were collected at the end of the workshop, the improvement could only have happened through collaboration with other workshop participants.

Importantly, the beneficial impacts of the workshop are not driven by one domain alone. Appendix Table A.8 shows that re-running the ITT regressions with basic controls but for resilience measured after removing one domain at a time delivers similar estimates for the treatment effect, underscoring the salience of collaboration, vision, and health domains.

8. **Medium-Term Impacts**

Response rates. Out of the 521 students in the treatment or control group, 87 students in the treatment group and 51 students in the control group students responded to the follow-up survey, this represents a response rate of 33.5 and 19.5 percent. In addition, fifty-one students who were neither assigned to treatment nor control groups also responded to the follow-up survey, representing a response rate of 10.7 percent. Not surprisingly, the follow-up survey response rate was higher for students who were assigned to the treatment group than to the control group than to the students who were not assigned to either group. It is important to underscore that despite differential response rates by treatment status, Table A.9 shows that all the demographic, neighborhood, educational, and mental health variables measured at baseline are balanced between the treatment- and control-group follow-up survey respondents. Nonetheless, given the smaller sample size among follow-up respondents, we ran a logit regression to explore which covariates are related to the likelihood of a student responding to the follow-up survey. Table A.10 shows that along with selection based on treatment, female students and students with lower baseline resilience are more likely to respond to the follow-up survey while students of a race other than Asian, Black, Hispanic, or white are less likely to respond. Importantly, columns 4 and 8 in Table A.10 show that once we control for students' baseline resilience and allow for differential treatment impact by students' baseline resilience level (as in our preferred specification), neither the coefficient on the treatment dummy nor the treatment interacted with baseline resilience are statistically significantly different from zero.

Raw Data. To see how resilience changed in the medium term relative to baseline, Appendix Figure A.2 shows densities for the distribution of resilience at baseline and in the medium term, by treatment status. Baseline resilience comes from the application survey while the medium-term resilience outcome is from the follow-up survey. Given the low response rate to the follow-up survey, we separate the baseline densities by whether the student responded to the follow-up survey and, thus, has a reported medium-term resilience. This shows possible selection into responding to the follow-up survey with students who did respond having lower resilience at application. However, even when only comparing the baseline and medium-term resilience of students who responded to the follow-up survey, medium-term resilience is lower for both students in the treatment and control groups but with a greater fall in resilience for students in the control group.

Medium-Term Impacts on Resilience. To study the medium-term effects of the intervention, we ran our main specification but with our left-hand-side variable measured between three and six months after the workshops took place. Results are shown in column 3 of Table 6. They show that the β_1 coefficient is still positive albeit about half the size than the short-run impact estimated earlier (also shown in column 1) and no longer statistically significant. The β_3 coefficient in Column 3 continues to be negative and of similar size as the short-run coefficient β_3, yet it lacks statistical precision. In both cases, the standard errors are considerably larger than in the short run.

Column 4 presents an alternative specification where instead of controlling for baseline resilience in a continuous way, we instead use a binary variable indicating whether the student's baseline resilience falls above or below the control-group median baseline resilience. For comparison reasons, column 2 presents estimates from the same specifications using, as the left-hand-side variable, the short-term resilience outcome, measured at the end of workshop. Column 2 shows an average short-run positive effect of the resilience-thinking workshop on students in the bottom half of the baseline resilience distribution, with no effect for students in the top half of the distribution (as +0.203-0.206=-0.003). Moving to medium-term effects, column 4 shows persistent beneficial medium-term impacts of the resilience-thinking workshop for students in the bottom half of the baseline resilience distribution. These beneficial medium-term impacts are statistically significant at the 10% level. As in the short-run, there is no average effect of the resilience-thinking workshop on the resilience of students in the top half of the baseline resilience distribution. Medium-term estimates are larger in size than shorter-term ones.

Appendix Table A.11 shows medium-term results by resilience domain. Consistent with short-term findings, the intervention was most impactful in changing students' collaboration, vision, and health (although for vision, there is also a detrimental effect for those in the top-half of the baseline distribution). As it is unlikely that a 90-minute intervention prompted long-lasting friendships among the students that participated in the same workshop, and because the intervention empowered students to act within their communities, it is more plausible that the observed medium-term impacts are driven by students' improved relationships outside of the experiment.

Medium-Term Impacts on Psychological Wellbeing. Table 7 shows the medium-term effects for the other mental health variables in the medium term. The outcome is the score for each variable (0-27 for depression, 0-21 for anxiety, and 0-5 for PTS), standardized with the baseline control-group mean score and standard deviation[22]. In each case, a higher score indicates more distress. Moving now to Table 7 results, we find that, unlike for resilience, there are no significant treatment effects in the medium-term on depression, anxiety, or PTS, and the size of the coefficients is generally smaller than the significant effects for medium-term resilience.

Medium-Term Impacts on Academic Impacts. In Fall 2023, we requested access to the academics of treated- and control-group students to estimate the impact of the intervention on academic performance measured as semester GPA during the semester of the intervention, and the following semester. Results are shown in Appendix Table 8. We find no evidence of an impact of the intervention on academic performance at the end of the semester or at the end of the subsequent semester as none of the coefficients are statistically significant. However, in contrast with the results on resilience, the sign of the coefficients would indicate a beneficial impact for students at the top-half of the baseline resilience distribution if we had had statistical significance. The lack of academic findings in low-touch interventions is not uncommon (see Oreopoulos & Petronijevic 2023).

9. Conclusion

We conducted a randomized evaluation of an in-depth group workshop where Queens College (QC) students were introduced to the resilient-thinking approach, which offers conceptual tools to cope with unexpected negative shocks. Treated youths were offered a 90-minute workshop where they identified challenges in their community both before and after the COVID-19 pandemic, and brainstormed strategies to address them. We find that the intervention increased

[22] The mean and standard deviation for PTS at baseline is divided by 16 since the score is 0-80 at baseline but 0-5 in the medium-term. As explained in the Data Section, we used the smaller set of questions from the PCPTSD-5 scale in the follow-up survey rather than the 20 questions from the PCL-5 scale that we used in the baseline survey. This was to reduce students' burden.

resilience of those in the bottom half of the baseline resilience distribution and this effect persists over time. This effect is mostly driven by an improvement on students' maintenance and formation of support networks and personal relationships (collaboration), and sense of purpose and belief in an ability to define, clarify and achieve goals (vision). This result is stronger for and impacts a larger share of Black and Hispanics, female students, first-generation students, transfer students, and juniors and seniors. We also find that the intervention is most effective among students with weaker individual protective factors (lower resilience and psychological wellbeing at baseline), yet the opposite is true for individuals with unreliable system protective factors as the intervention is more effective for those with stronger community protective factors. These results suggest that individual and community protective factors mediate differently within this intervention. While we did not find medium-term effects on other mental health outcomes or academic performance, the persistent effects on resilience suggest that such type of intervention may be a relatively cost-effective tool to pre-emptively boost students' resilience, which is known to improve mental health (Singer 2009; Göran & Whitehead 1991; Sachs et al 2020) and students' wellbeing. Alternatively, a more intensive intervention may also be easy to implement and deliver broader and more persistent results.

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Tables and Figures for "Resilience-Thinking Training for College Students: Evidence from a Randomized Trial"

Figure 1: Resilience-Thinking-Training (RTT) Workshops at Queens College, Year 2022

Figure 2: Distribution of Baseline Resilience for Treatment and Control Groups

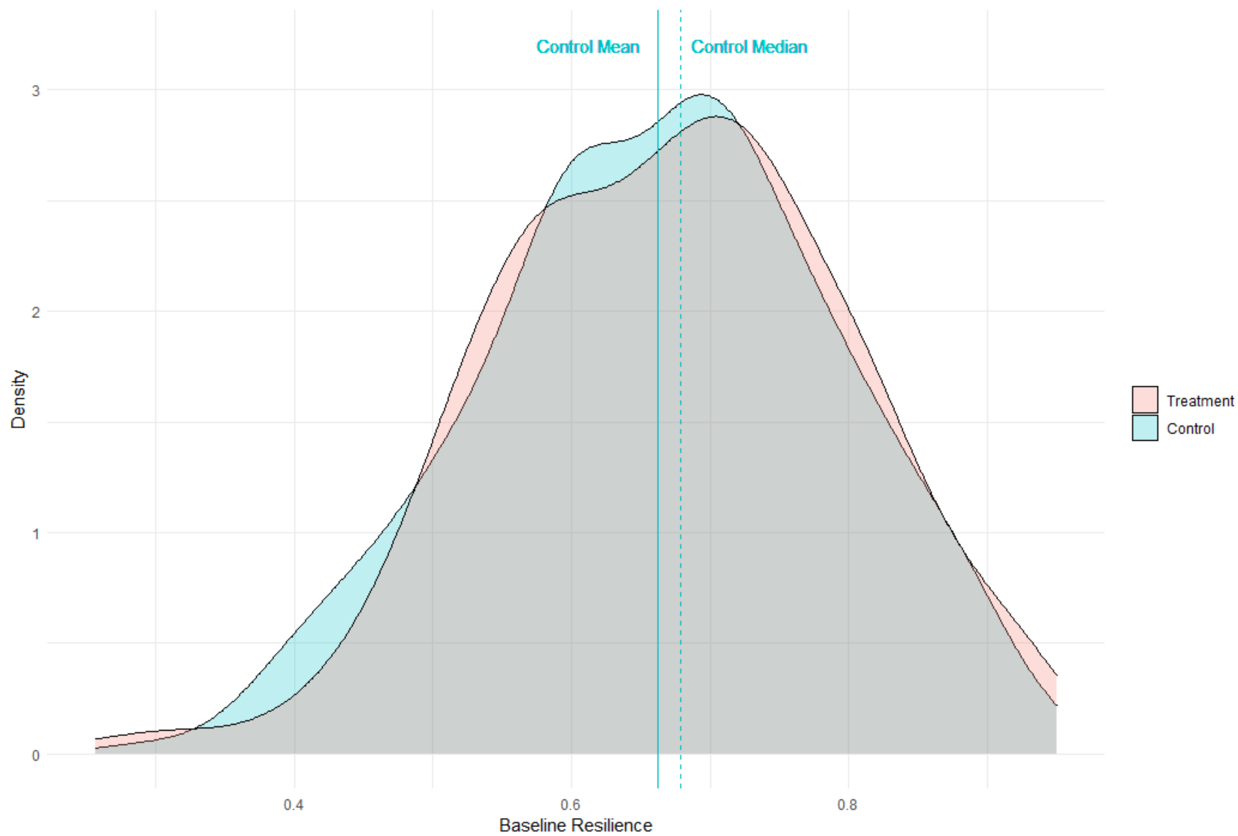
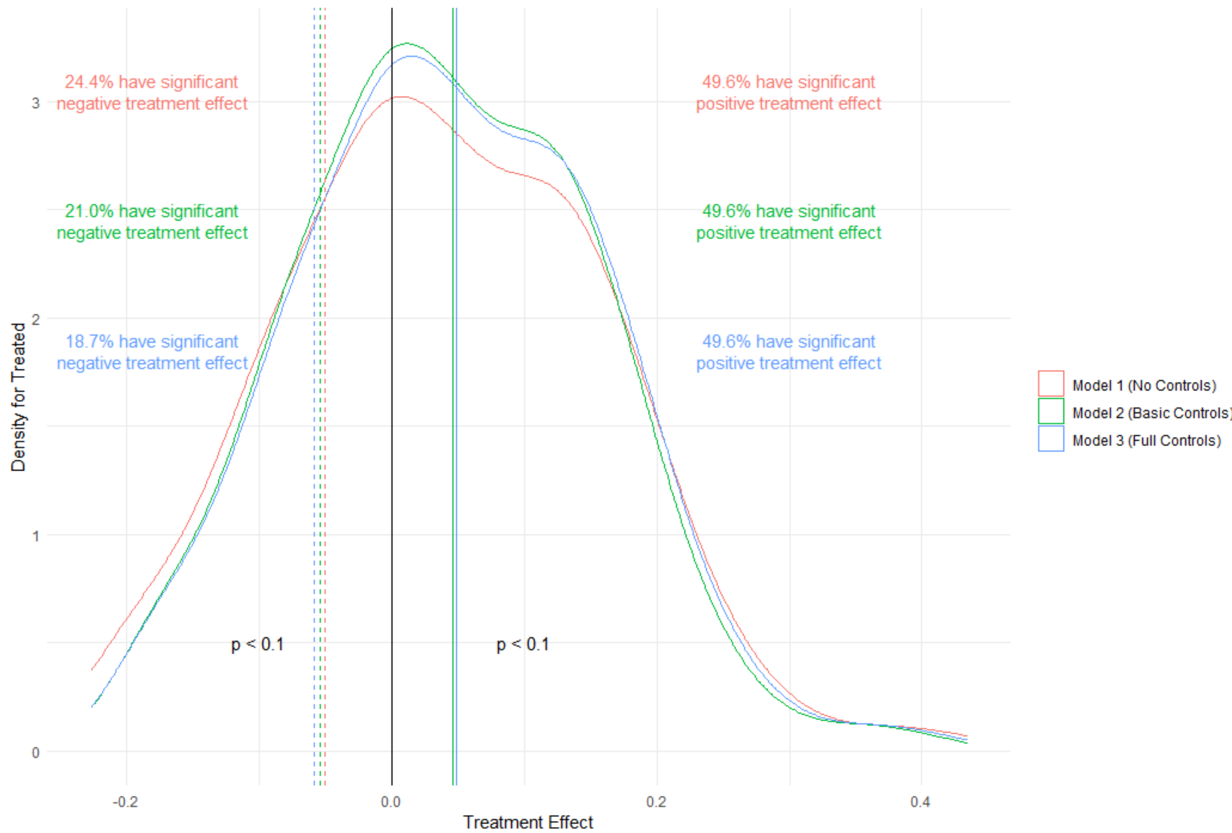
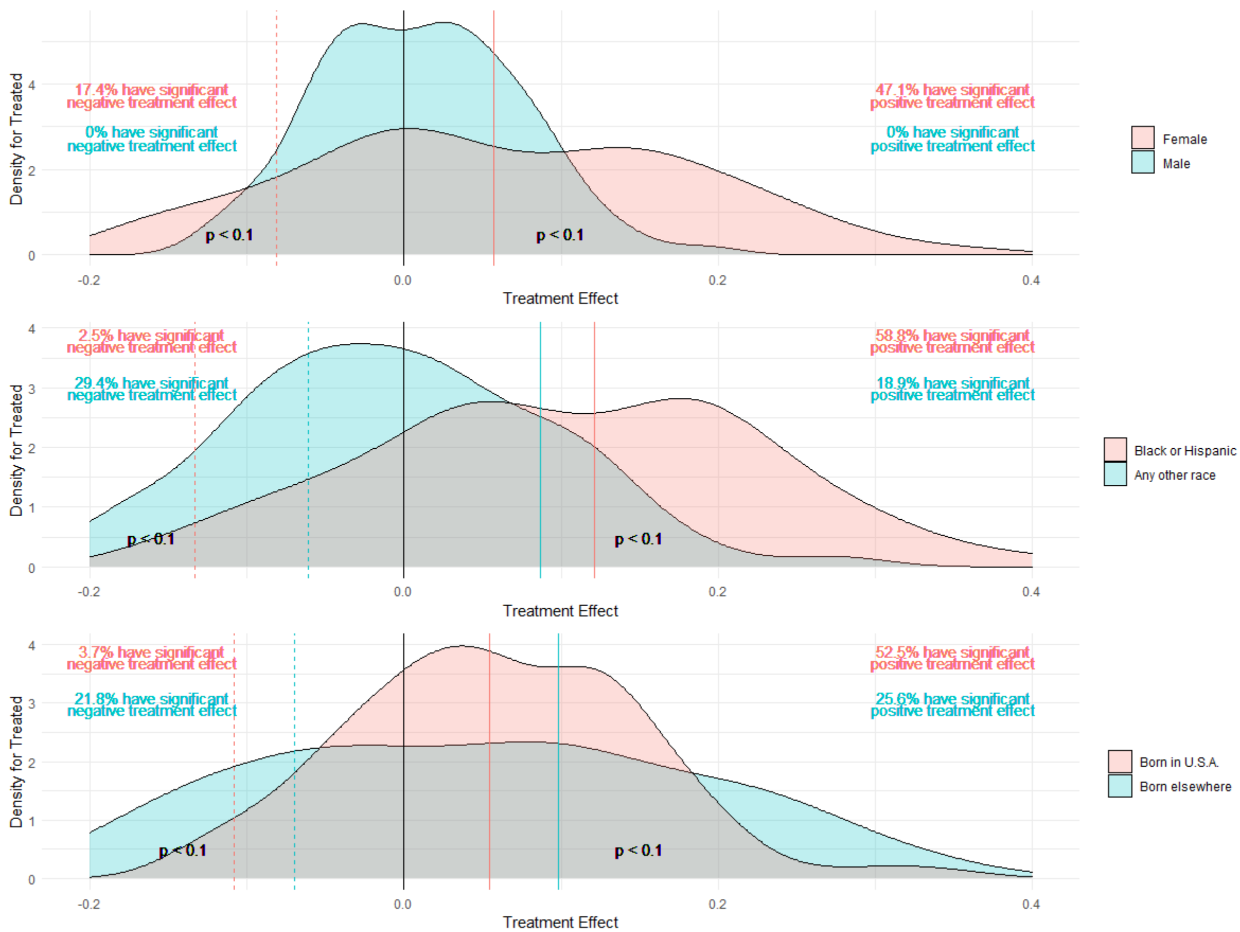


Figure 3: Distribution of Treatment Effects based on Treated Students' Baseline Resilience



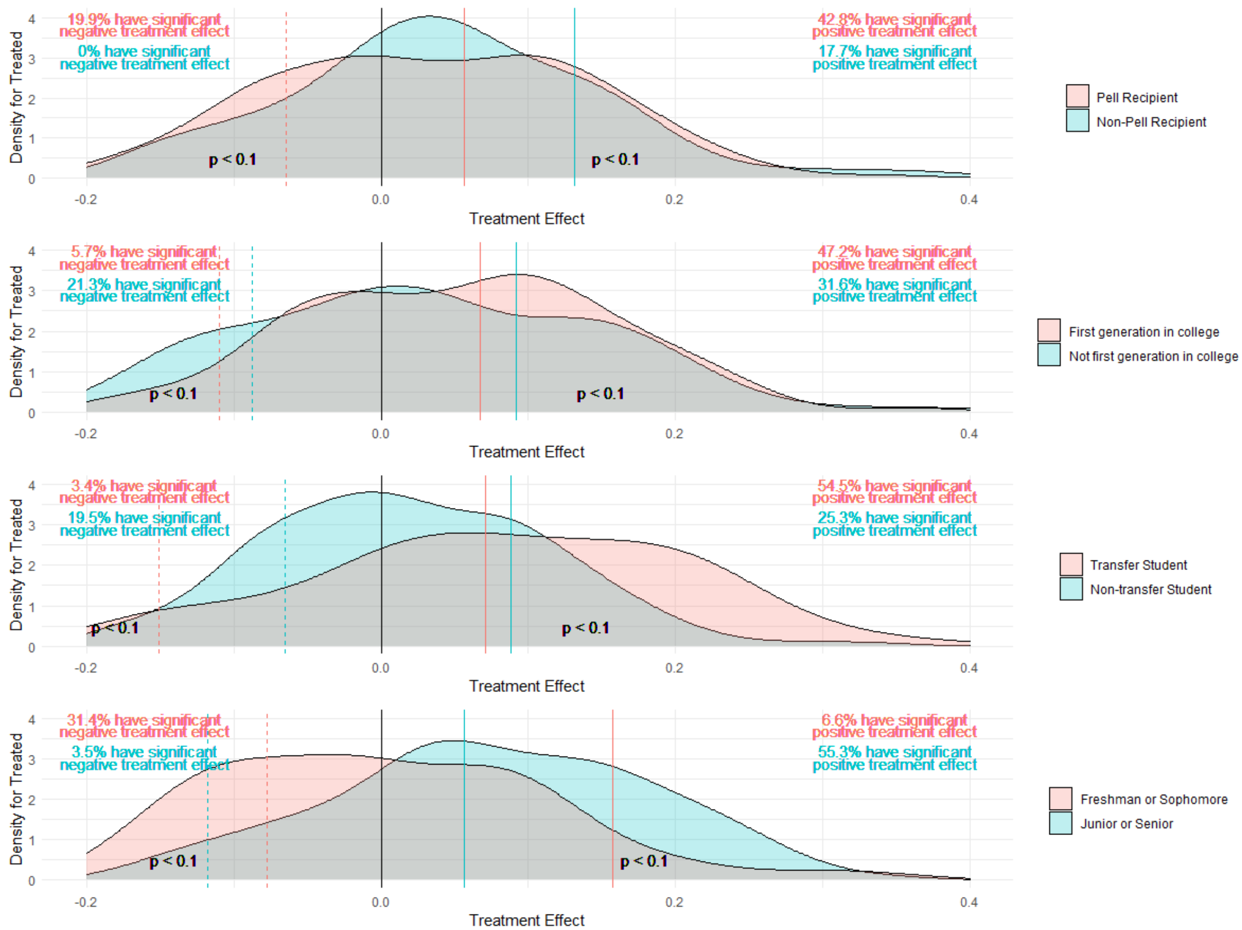
Notes: Treatment effects come from plugging in each treated student's pre-resilience into the formula, $\beta_1 + \beta_3 \times Pre - Resilience$. Estimated values for β_1 and β_3 come from columns 1, 2, and 5 in Table 3.

Figure 4: Distribution of Treatment Effects for Treated by Sex, Race, and National Origin



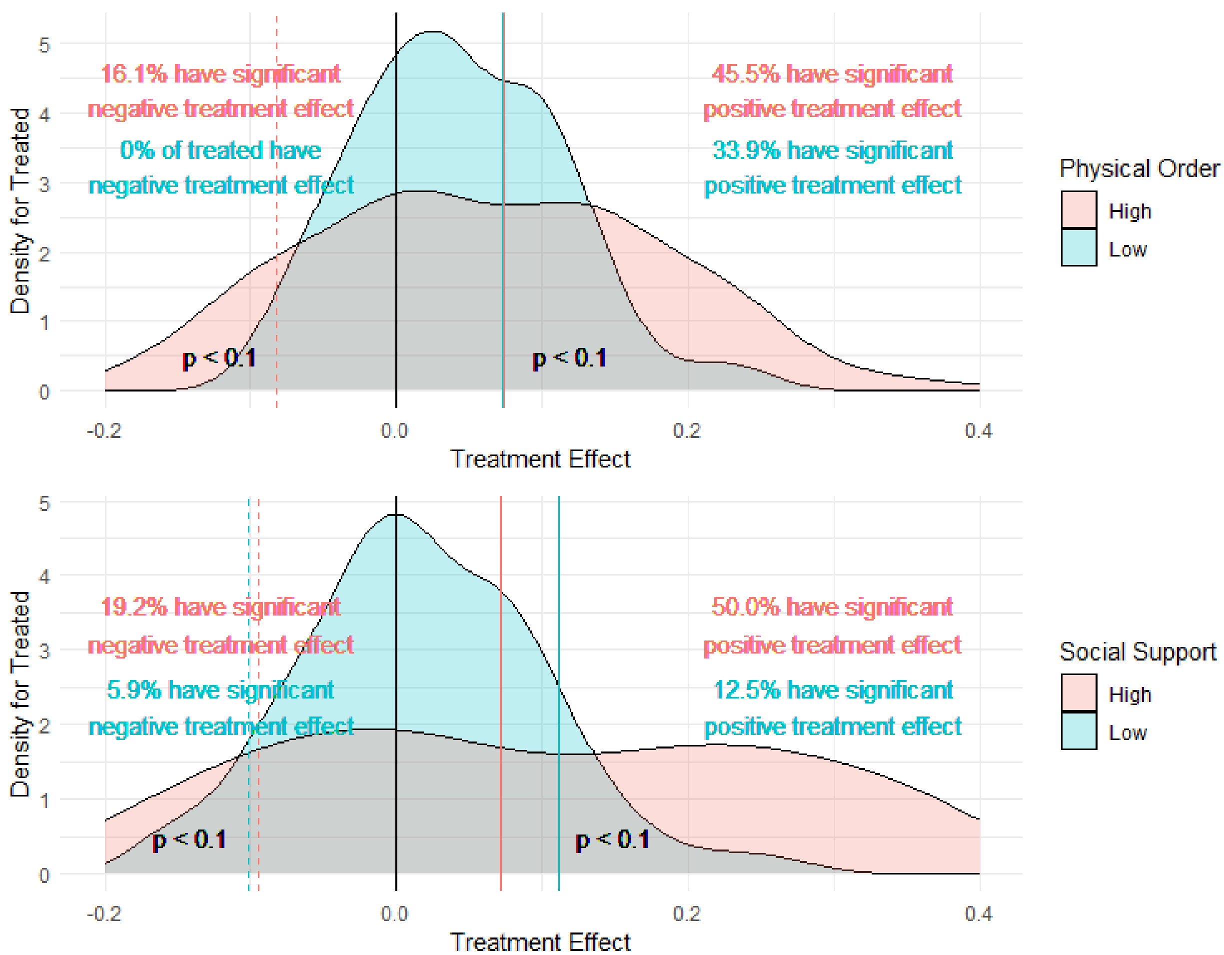
Notes: Treatment effects come from plugging in each treated student's pre-resilience into the formula, $\beta_1 + \beta_3 \times Pre - Resilience$. Estimated values for β_1 and β_3 come from estimating our preferred specification (as in column 2 of Table 3) separately by subgroup. Sample Sizes for each subgroup are: Female = 343, Male = 178; Black or Hispanic = 233, Any other race = 288; Born in U.S.A. = 327, Born elsewhere = 145

Figure 5: Distribution of Treatment Effects for Treated by Academic Status



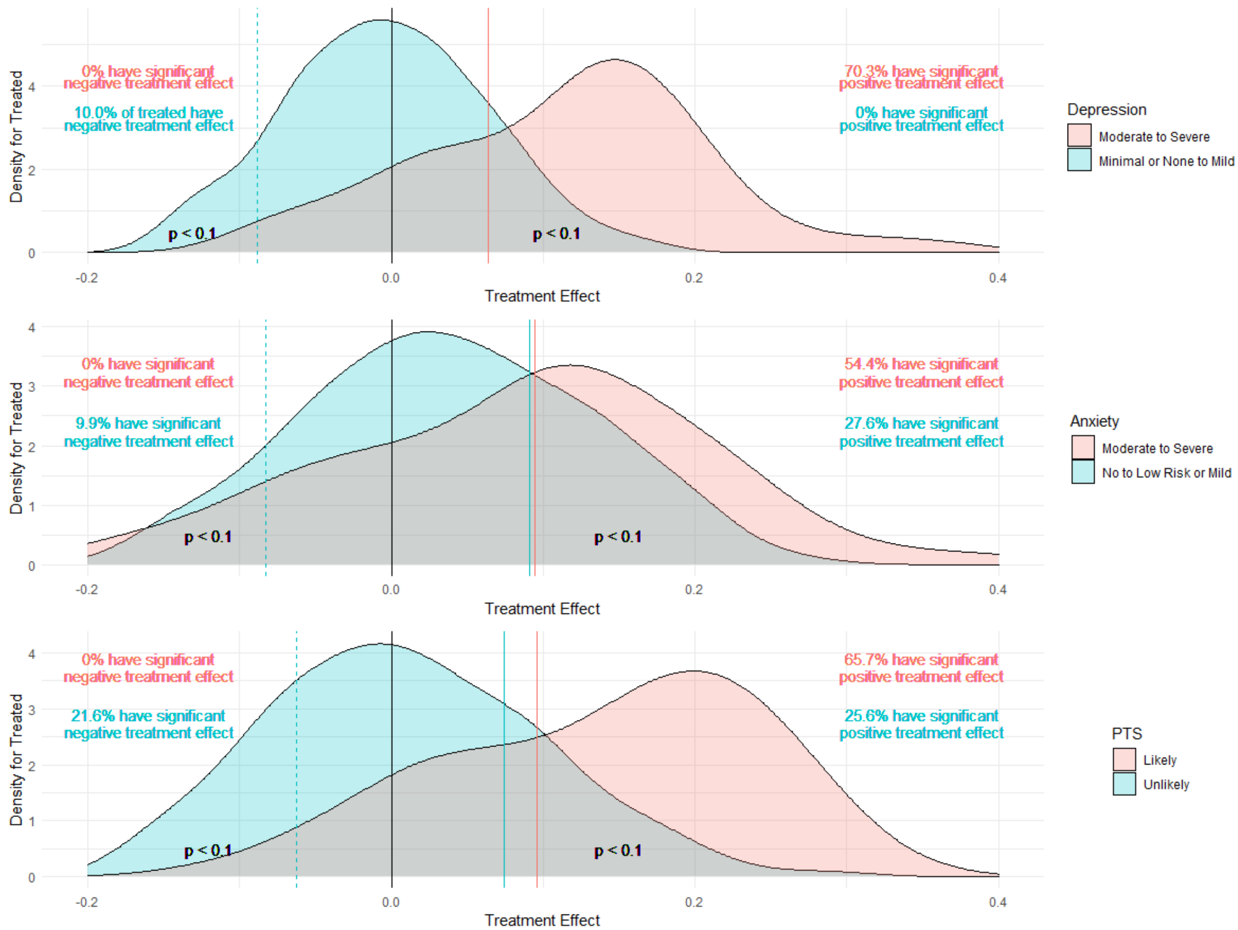
Note: Treatment effects come from plugging in each treated student's pre-resilience into the formula, $\beta_1 + \beta_3 \times Pre - Resilience$. Estimated values for β_1 and β_3 come from estimating our preferred specification (as in column 2 of Table 3) separately by subgroup. Sample sizes for each subgroup are: Pell = 327, Non-Pell = 194; First Generation = 208, Not First Generation = 263; Transfer = 189, Non-transfer = 332; Freshman or Sophomore = 238, Junior or Senior = 283

Figure 6: Distribution of Treatment Effects for Treated by Social Capital



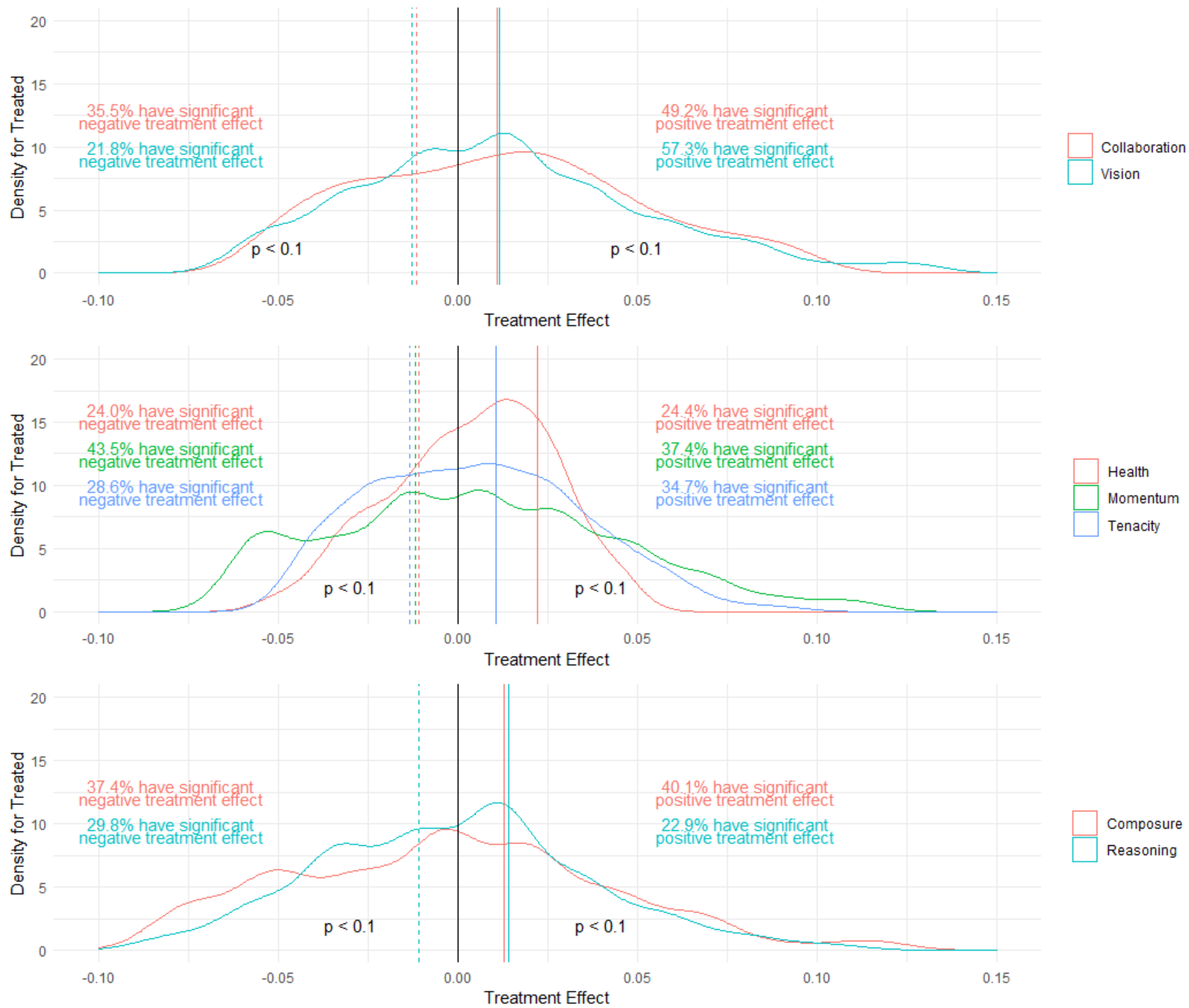
Note: Treatment effects come from plugging in each treated student's pre-resilience into the formula, $\beta_1 + \beta_3 \times Pre - Resilience$. Estimated values for β_1 and β_3 come from estimating our preferred specification (as in column 2 of Table 3) separately by subgroup. Sample sizes for each subgroup are: High Physical Order = 268, Low Physical Order = 240; High Social Support = 213, Low Social Support = 294

Figure 7: Distribution of Treatment Effects for Treated by Mental Health



Note: Treatment effects come from plugging in each treated student's pre-resilience into the formula, $\beta_1 + \beta_3 \times Pre - Resilience$. Estimated values for β_1 and β_3 come from estimating our preferred specification (as in column 2 of Table 3) separately by subgroup. Sample sizes for each subgroup are: Depression Likely = 206, Depression Unlikely = 284; Anxiety Likely = 163, Anxiety Unlikely = 326; PTS Likely = 130, PTS Unlikely = 345

Figure 8: Distribution of Treatment Effects for Treated by Resilience Domain



Note: Treatment effects come from plugging in each treated student's baseline score for each domain into the formula, $\beta_1 + \beta_3 * DomainScore$. Estimated values for β_1 and β_3 are different for each domain and come from the relevant columns in Appendix Table A.7.

Table 1: Baseline Characteristics and Balance Tests

Variable	In Treatment	In Control	Diff.[a]	# Obs.	Enrolled at QC Fall 2021[b]	Hispanic SIs in 2019[c]
Female	0.656	0.66	-0.004 (0.042)	521	0.541	
Asian	0.286	0.324	-0.038 (0.04)	521	0.308	0.083
Black	0.103	0.112	-0.009 (0.027)	521	0.088	0.090
Hispanic	0.351	0.328	0.023 (0.042)	521	0.289	0.490
White	0.134	0.127	0.006 (0.029)	521	0.233	0.246
Other Race	0.126	0.108	0.018 (0.028)	521	0.082	
College Age (< 23)	0.756	0.764	-0.009 (0.038)	521	0.680	
Freshman or Sophomore	0.462	0.452	0.01 (0.044)	521	0.358[d]	
Pell Grant Recipient	0.634	0.622	0.012 (0.042)	521	0.481[d]	
Born in U.S.A.	0.675	0.711	-0.037 (0.043)	472	0.722	
First Generation	0.438	0.445	-0.009 (0.046)	471	0.358[d]	
Transfer	0.336	0.39	-0.054 (0.042)	521	0.229	
Part-Time	0.172	0.158	0.014 (0.032)	521	0.277	
Physical Order (0 to high of 3)	1.987	1.922	0.065 (0.044)	508		
Social Support (0 to high of 3)	0.961	1.005	-0.046 (0.065)	507		
GPA[g] (0 to high of 4)	2.937	3.044	-0.108 (0.113)	355		
Depression Likely (Moderate to Severe)	0.402	0.448	-0.046 (0.045)	490	0.402[e]	
Anxiety Likely (Moderate to Severe)	0.273	0.398	-0.125*** (0.042)	490	0.325[e]	
PTS Likely (Satisfies Diagnostic Rule)	0.276	0.276	0 (0.041)	475	0.271[ef]	
Resilience[h] (0.2 to 1 on 6 Predictive Factor Resilience Scale)	0.671 (0.126)	0.662 (0.126)	0.009 (0.012)	521	-	

Note: Significantly different at the 10(*), 5(**), and 1(***)% level

[a] Coefficient (standard error in parentheses below) on treatment dummy from OLS regression of row variable on treatment and a dummy for semester

[b] From Fall 2021 Enrolled Student Profile table for undergraduates at QC. Source: https://public.tableau.com/app/profile/qc.oie/viz/1_CollegeProfile-EnrolledStudents/EnrolledStdntProfile

[c] Hispanic Serving Institutions (HSIs) are colleges and universities with Hispanic populations at least 25% of undergraduate students. Enrollment at HSIs by race is from 2019 report from American Council on Education. Source: https://www.equityinhighered.org/wp-content/uploads/2019/02/Race-and-Ethnicity-in-Higher-Education.pdf

[d] From summer 2020 sample (N = 3,163) of Queens College students (Rodríguez-Planas 2022a).

[e] From April 2020 sample (N = 2,925) of CUNY students (Rudenstine et al. 2021b).

[f] Based off of PC-PTSD 4-item scale

[g] Student's GPA for the semester before the workshop which is Fall 2021 for students who took the workshop in Spring 2022 and Spring 2022 for students who took the workshop in Fall 2022.

[h] Standard deviations for treatment and control shown in parentheses. Sample includes 42 observations with missing responses to 1 or 2 questions used to calculate resilience (and 2 more observations in the control group with more missing responses) for which we use information from their other responses to fill in.

Table 2: Likelihood of Attending Workshop

	Dependent variable:	
	Attended	
	(1)	(2)
SemesterSpring2022	0.228	0.050
	(0.290)	(0.305)
Female	0.223	0.149
	(0.272)	(0.300)
Asian	0.334	0.334
	(0.437)	(0.470)
Black	1.318**	1.525**
	(0.574)	(0.626)
Hispanic	0.491	0.568
	(0.422)	(0.448)
OtherRace	0.116	0.295
	(0.516)	(0.618)
CollegeAge	0.457	0.445
	(0.405)	(0.435)
Underclassman	−0.093	−0.214
	(0.284)	(0.307)
Pell	−0.237	−0.374
	(0.291)	(0.323)
USA		0.320
		(0.341)
FirstGen		−0.014
		(0.293)
Transfer	−0.131	−0.010
	(0.352)	(0.380)
PartTime	−0.331	−0.528
	(0.399)	(0.435)
DepressionLikely		−0.267
		(0.372)
AnxietyLikely		0.207
		(0.408)
PTSLikely		0.127
		(0.385)
Constant	−0.598	−0.529
	(0.601)	(0.701)
Observations	262	234
Log Likelihood	−173.813	−152.814
Akaike Inf. Crit.	371.627	339.629

*p<0.1; **p<0.05; ***p<0.01

Note: Estimates in each column are from Logit regressions for the set of students that are treated. The dependent variable is a dummy for if the student attended the workshop. Both columns include as controls a dummy for if the workshop was in the spring semester, dummies for whether the student is female, Asian, Black, Hispanic, or another race, younger than 23 years old, a freshman or a sophomore, a Pell recipient, a transfer student, or a part-time student. The second column adds more controls including dummies whether the student was born in the United States or not, whether the student is a first-generation college student or not, and dummies for whether the student has moderate to severe depression or anxiety on the PHQ-9 and GAD-7 scales and a dummy for whether a student satisfies the DSM-5 diagnostic rule on the PCL-5 20-item scale for PTS.

Table 3: Intention-to-Treat Effect on Short-Term Resilience

	Dependent variable: Short-Term Resilience					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.048*	0.050*	0.050*	0.061**	0.053*	0.043
	(0.028)	(0.028)	(0.030)	(0.030)	(0.030)	(0.029)
Treatment×Resilience	−0.120***	−0.111***	−0.112***	−0.112***	−0.113***	−0.088***
	(0.030)	(0.030)	(0.030)	(0.032)	(0.032)	(0.030)
Basic Controls		X	X	X	X	X
Workshop Dummies			X			
Remove NAs for MH				X	X	
MH Controls					X	
Complete Resilience						X
Observations	521	521	521	460	460	478
R^2	0.899	0.901	0.903	0.891	0.892	0.909
Adjusted R^2	0.898	0.898	0.899	0.888	0.888	0.906

*p<0.1; **p<0.05; ***p<0.01

Note: Estimates in each column are from OLS regressions of short-term resilience on a treatment dummy, baseline resilience, their interaction, and a semester dummy. Baseline resilience and short-term resilience are each standardized by the distribution of baseline resilience for the control group. Basic controls include dummies for whether the student is female, Asian, Black, Hispanic, or another race, younger than 23 years old, a freshman or a sophomore, a Pell recipient, a transfer student, or a part-time student. Column 5 adds mental health (MH) controls which are dummies for whether the student has moderate to severe depression or anxiety on the PHQ-9 and GAD-7 scales and a dummy for whether a student satisfies the DSM-5 diagnostic rule on the PCL-5 20-item scale for PTS. Column 4 omits any observations with a missing value for the 3 mental health controls. Column 6 throws out observations with any non-response to questions used to calculate pre- (42 observations) and short-term (1 observation) resiliences. All regressions use robust standard errors with those reported in parentheses below the estimates.

Table 4: Intention-to-Treat Effect for Bottom and Top Quartile Baseline Resilience

Group	Percentile of Group's Baseline Resilience 25th	75th
Whole Sample	0.12^{***}	-0.03
Female	0.15^{***}	-0.03
Male	0.05	-0.04
Black or Hispanic	0.19^{***}	0.03
Any other race	0.06	-0.08^{*}
Born in U.S.A.	0.13^{**}	-0.01
Born elsewhere	0.13^{*}	-0.11
Pell Recipient	0.12^{**}	-0.04
Non-Pell Recipient	0.12	-0.02
First generation in college	0.13^{**}	-0.03
Not first generation in college	0.12^{*}	-0.07
Transfer student	0.18^{***}	0.00
Non-transfer student	0.09^{*}	-0.05
Freshman/Sophomore	0.08	-0.11^{**}
Junior/Senior	0.16^{***}	0.01

Note: Significant at the 10(*), 5(**), and 1(***)% level
Treatment effects reported in standard deviations (of the control group's baseline resilience) meaning that a 0.10 treatment effect raises resilience by 10% of a standard deviation. Treatment effects come from plugging in the 25th and 75th percentile of pre-resilience for students in the relevant group that were also in the treatment group into the formula, $\beta_1 + \beta_3 \times Pre - Resilience$. Estimated values for β_1 and β_3 come from estimating our preferred specification (as in column 2 of Table 3) separately by subgroup.

Table 5: Intention-to-Treat Effect for Bottom and Top Quartile Baseline Resilience

	Percentile of Group's Baseline Resilience	
Group	25th	75th
High Physical Order	0.14^{**}	-0.03
Low Physical Order	0.09^{*}	-0.01
High Social Support	0.24^{***}	-0.07
Low Social Support	0.07	-0.03
Depression Likely	0.17^{***}	0.04
Depression Unlikely	0.04	-0.05
Anxiety Likely	0.18^{**}	-0.00
Anxiety Unlikely	0.11^{**}	-0.03
PTS Likely	0.18^{**}	-0.00
PTS Unlikely	0.07^{*}	-0.06

Note: Significant at the 10(*), 5(**), and 1(***)% level
Treatment effects reported in standard deviations (of the control group's baseline resilience) meaning that a 0.10 treatment effect raises resilience by 10% of a standard deviation. Treatment effects come from plugging in the 25th and 75th percentile of pre-resilience for students in the relevant group that were also in the treatment group into the formula, $\beta_1 + \beta_3 \times Pre - Resilience$. Estimated values for β_1 and β_3 come from estimating our preferred specification (as in column 2 of Table 3) separately by subgroup.

Table 6: Intention-to-Treat Effect on Short- vs Medium-Term Resilience

	Dependent variable: Resilience			
	Short-Term		Medium-Term	
	(1)	(2)	(3)	(4)
Treatment	0.050*	0.203**	0.027	0.350*
	(0.028)	(0.088)	(0.123)	(0.197)
Resilience	0.997***		0.893***	
	(0.004)		(0.091)	
ResilienceHigh		1.599***		1.718***
		(0.075)		(0.199)
Treatment×Resilience	−0.111***		−0.116	
	(0.030)		(0.118)	
Treatment×ResilienceHigh		−0.206*		−0.409
		(0.114)		(0.269)
Observations	521	521	138	138
R^2	0.901	0.592	0.654	0.523
Adjusted R^2	0.898	0.581	0.615	0.469

*p<0.1; **p<0.05; ***p<0.01

Note: Estimates in each column are from OLS regressions of short- or medium-term resilience on a semester dummy and basic controls along with the other variables listed in the table. Baseline, short-term, and medium-term resilience are each standardized by the distribution of baseline resilience for the control group. Basic controls include dummies for whether the student is female, Asian, Black, Hispanic, or another race, younger than 23 years old, a freshman or a sophomore, a Pell recipient, a transfer student, or a part-time student. Resilience High is a dummy for whether baseline resilience is greater than the median for the control group. All regressions use robust standard errors with those reported in parentheses below the estimates.

Table 7: Intention-to-Treat Effects on Medium-Term Mental Health

	Dependent variable:			
	Resilience	Depression	Anxiety	PTS
Treatment	0.350^{*}	0.030	−0.184	−0.037
	(0.197)	(0.254)	(0.283)	(0.431)
ResilienceHigh	1.718^{***}	-0.856^{***}	-1.017^{***}	−0.365
	(0.199)	(0.302)	(0.316)	(0.447)
Treatment×ResilienceHigh	−0.409	−0.087	−0.024	−0.330
	(0.269)	(0.346)	(0.400)	(0.544)
Observations	138	128	129	130
R^2	0.523	0.247	0.271	0.138
Adjusted R^2	0.469	0.154	0.181	0.033

*p<0.1; **p<0.05; ***p<0.01

Note: Estimates in each column are from OLS regressions of medium-term mental health variables on a semester dummy and basic controls along with the other variables listed in the table. Baseline resilience and all of the medium-term mental health variables are each standardized by the distribution of the relevant baseline mental health variable for the control group. Basic controls include dummies for whether the student is female, Asian, Black, Hispanic, or another race, younger than 23 years old, a freshman or a sophomore, a Pell recipient, a transfer student, or a part-time student. Resilience High is a dummy for whether baseline resilience is greater than the median for the control group. All regressions use robust standard errors with those reported in parentheses below the estimates.

Table 8: Intention-to-Treat Effects on Semester GPA

	Dependent variable: Semester GPA			
	Semester of Workshop		Following Semester	
	(1)	(2)	(3)	(4)
Treatment	0.051	−0.043	−0.078	−0.193
	(0.086)	(0.118)	(0.107)	(0.154)
Resilience	−0.052		−0.029	
	(0.064)		(0.072)	
ResilienceHigh		−0.053		−0.007
		(0.128)		(0.149)
Treatment×Resilience	0.093		0.090	
	(0.088)		(0.104)	
Treatment×ResilienceHigh		0.199		0.248
		(0.179)		(0.219)
Observations	493	493	476	476
R^2	0.060	0.061	0.099	0.103
Adjusted R^2	0.033	0.033	0.072	0.075

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: Estimates in each column are from OLS regressions of semester GPA on a semester dummy and basic controls along with the other variables listed in the table. Baseline resilience is standardized by the distribution of the resilience for the control group. Basic controls include dummies for whether the student is female, Asian, Black, Hispanic, or another race, younger than 23 years old, a freshman or a sophomore, a Pell recipient, a transfer student, or a part-time student. Resilience High is a dummy for whether baseline resilience is greater than the median for the control group. Semester of Workshop refers to the GPA received by students at the end of the semester in which they took the workshop. The following semester refers to the GPA in the next semester which for students that took the workshop in Spring 2022 is the Fall 2022 semester and for students that took the workshop in Fall 2022 is the Spring 2023 semester. All regressions use robust standard errors with those reported in parentheses below the estimates.

Appendix: Additional Tables and Figures

Figure A.1: Spider Diagram on Student's Perceived Challenges Pre- and Post-Pandemic, Queens College 2022

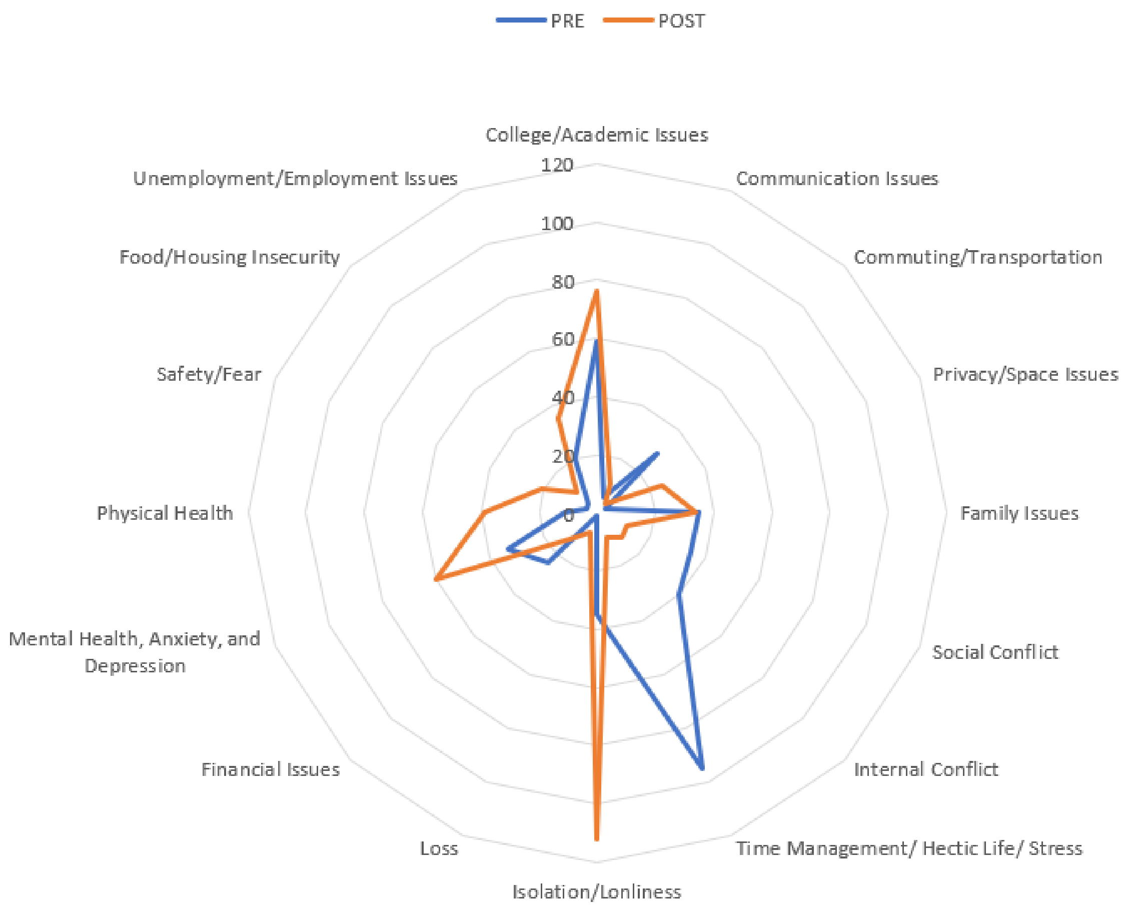
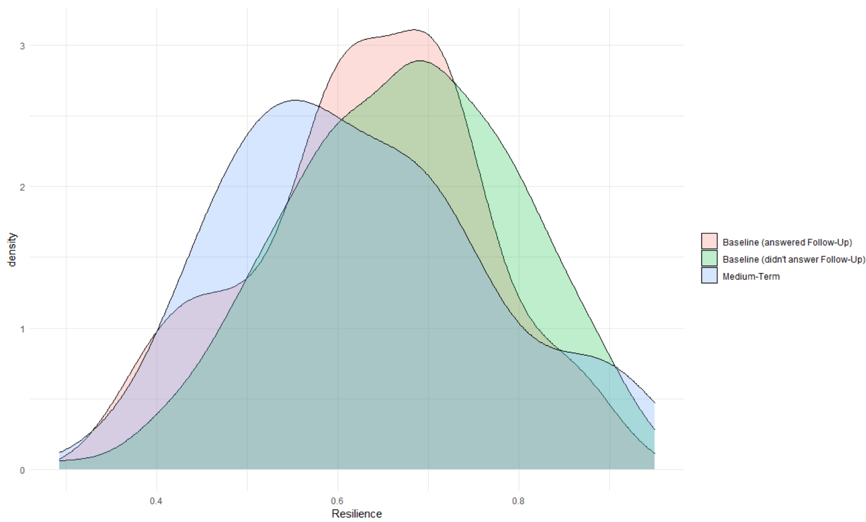
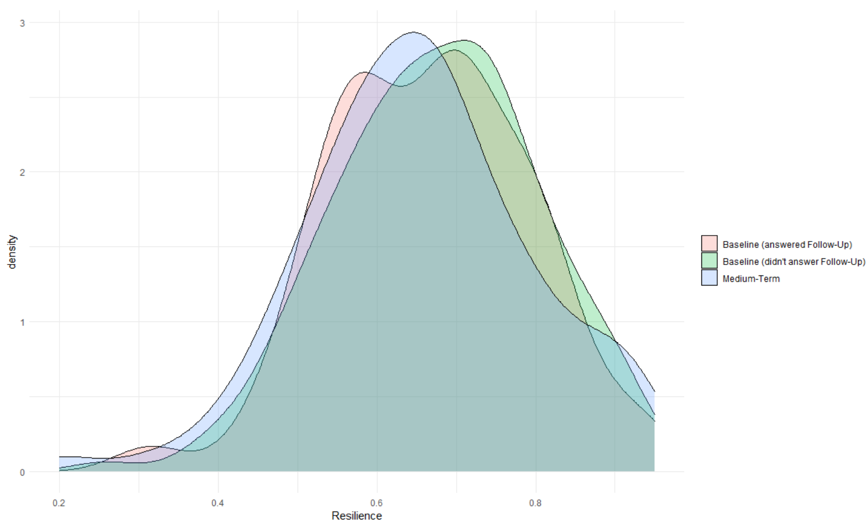


Figure A.2: Distribution of Resilience at Baseline and Medium-Term

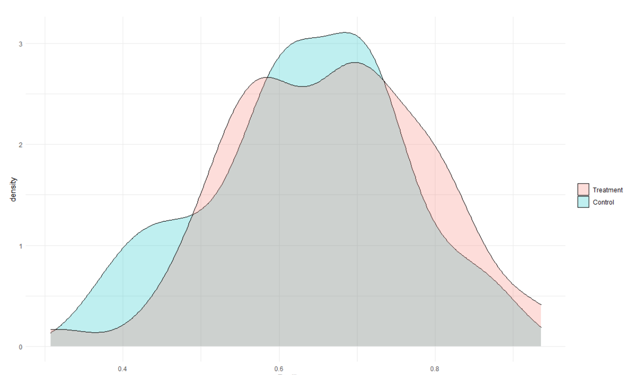
(a) Control Group



(b) Treatment Group



(c) Treatment vs. Control at Baseline (answered Follow-Up)



Notes: Baseline resilience comes from the application survey while medium-term resilience comes from the follow-up survey. The density for baseline resilience is broken up by whether the student responded to the follow-up survey and thus has a reported medium-term resilience.

Table A.1: Categories and Questions for Depression Index (PHQ-9 Scale)

Categories	Total score out of 27 from adding up each response (0-3) for all 9 statements
Minimial or None	0-4
Mild	5-9
Moderate	10-14
Moderately Severe	15-19
Severe	20-27
Prompt	Over the LAST TWO WEEKS, how often have you been bothered by any of the following problems?
Responses	Not At All (0) Several Days (1) More than Half the Days (2) Nearly Every Day (3)
Questions	Statements
1	Little interest or pleasure in doing things
2	Feeling down, depressed, or hopeless
3	Trouble falling or staying asleep, or sleeping too much
4	Feeling tired or having little energy
5	Poor appetite or overeating
6	Feeling bad about yourself - or that you are a failure or have let yourself or your family down
7	Trouble concentrating on things, such as reading the newspaper or watching television
8	Moving or speaking so slowly that other people could have noticed. Or the opposite - being so fidgety or restless that you have been moving around a lot more than usual
9	Thoughts that you would be better off dead, or hurting yourself

Table A.2: Categories and Questions for Anxiety Index (GAD-7 Scale)

Categories	Total scores out of 21 by adding up each response (0-3) for all 7 statements
No to Low Risk	0-4
Mild	5-9
Moderate	10-14
Severe	15+
Prompt	Over the LAST TWO WEEKS, how often have you been bothered by any of the following problems?
Responses	Not At All (0) Several Days (1) More than Half the Days (2) Nearly Every Day (3)
Questions	Statements
1	Feeling nervous, anxious, or on edge
2	Not being able to stop or control worrying
3	Worrying too much about different things
4	Trouble relaxing
5	Being so restless that it's hard to sit still
6	Becoming easily annoyed or irritable
7	Feeling afraid as if something awful might happen

Table A.3: Categories and Questions for PTS Index (PCL-5 Scale)

Categories	Definition
Likely PTSD under the DSM-5 Diagnostic Rule	Treat response of 2 or higher as symptom endorsed for each question and for likely PTSD diagnosis require 1 endorsed item each in question clusters 1-5 and 6-7 and 2 endorsed items each in question clusters 8-14 and 15-20
Probable PTSD	Total scores out of 80 by adding up each response (0-4) for all 20 statements and use cutoff score of 31-33 with at or above cutoff being probable PTSD
Prompt	Below is a list of problems that people sometimes have in response to a very stressful experience. Please read each problem carefully and indicate how much you have been bothered by that problem in the PAST MONTH:
Responses	Not At All (0) A Little Bit (1) Moderately (2) Quite A Bit (3) Extremely (4)
Questions	Statements
1	Repeated, disturbing, and unwanted memories of the stressful experience?
2	Repeated, disturbing dreams of the stressful experience?
3	Suddenly feeling or acting as if the stressful experience was actually happening again (as if you were actually back there reliving it)?
4	Feeling very upset when something reminded you of the stressful experience?
5	Having strong physical reactions when something reminded you of the stressful experience (for example, heart pounding, trouble breathing, sweating)?
6	Avoiding memories, thoughts, or feelings related to the stressful experience?
7	Avoiding external reminders of the stressful experience (for example, people, places, conversations, activities, objects, or situations)?
8	Trouble remembering important parts of the stressful experience?
9	Having strong negative beliefs about yourself, other people, or the world (for example, having thoughts such as: I am bad, there is something seriously wrong with me, no one can be trusted, the world completely dangerous)?
10	Blaming yourself or someone else for the stressful experience or what happened after it?
11	Having strong negative feelings such as fear, horror, anger, guilt, or shame?
12	Loss of interest in activities that you used to enjoy?
13	Feeling distant or cut off from other people?
14	Trouble experiencing positive feelings (for example, being unable to feel happiness or have loving feeling for people close to you)?
15	Irritable behavior, angry outbursts, or acting aggressively?
16	Taking too many risks or doing things that could cause you harm?
17	Being “super-alert” or watchful or on guard?
18	Feeling jumpy or easily startled?
19	Having difficulty concentrating?
20	Trouble fall or staying asleep?

Table A.4: Social Capital Questions

Category	Questions
Physical Order	(1) There are trees along the streets in my neighborhood. (2) My neighborhood is generally free from litter. (3) There are many attractive natural sights in my neighborhood (such as landscaping, views). (4) There are attractive buildings/homes in my neighborhood. (5) It is easy to walk to a transit stop (bus, train) from my home. (6) My neighborhood streets are well lit at night. (7) There is a high crime rate in my neighborhood. (8) I have access to public parks near my neighborhood.
Social Support	(1) How likely are people in your neighborhood willing to help their neighbors with routine activities such as picking up their trash cans or helping to shovel snow? (2) How many local groups or organizations in your neighborhood do you currently belong to (such as social, political, religious, school-related, or athletic organizations)? (3) How often do people in your neighborhood work together to improve your neighborhood (such as picking up litter, planting flowers)?

Table A.5: Follow-Up Mental Health for Non-Treated Students

	Dependent variable:					
	ResilienceIndex		DepressionLikely		DepressionScore	
	(1)	(2)	(3)	(4)	(5)	(6)
Follow-Up	−0.111	−0.147	0.053	0.116	−0.124	−0.111
	(0.165)	(0.152)	(0.328)	(0.356)	(0.157)	(0.158)
SemesterSpring2022		0.018		0.171		0.060
		(0.157)		(0.378)		(0.169)
Female		−0.176		0.584		0.202
		(0.177)		(0.384)		(0.157)
Asian		-0.711^{**}		0.384		0.578^{**}
		(0.306)		(0.684)		(0.261)
Black		−0.061		0.774		0.688^{**}
		(0.413)		(0.811)		(0.316)
Hispanic		−0.112		−0.255		0.316
		(0.303)		(0.702)		(0.257)
OtherRace		−0.194		0.517		0.340
		(0.343)		(0.828)		(0.332)
CollegeAge		-0.662^{***}		0.716		0.446^{**}
		(0.218)		(0.533)		(0.218)
Underclassman		0.266		-0.955^{**}		−0.123
		(0.206)		(0.475)		(0.218)
Pell		-0.595^{***}		0.161		−0.063
		(0.172)		(0.403)		(0.190)
Transfer		0.230		−0.516		0.015
		(0.216)		(0.505)		(0.233)
PartTime		−0.242		−0.141		−0.002
		(0.222)		(0.538)		(0.207)
Constant	0.053	1.179^{**}	−0.235	−0.971	−0.004	-0.847^{**}
	(0.110)	(0.455)	(0.233)	(0.980)	(0.108)	(0.415)
Individual Fixed Effects	Yes	No	Yes	No	Yes	No
Observations	170	168	154	152	154	152
R^2	0.003	0.201			0.004	0.074
Adjusted R^2	−0.003	0.139			−0.002	−0.006
Log Likelihood			−105.899	−98.316		
Akaike Inf. Crit.			215.798	222.632		

*p<0.1; **p<0.05; ***p<0.01

Note: Estimates in each column are from OLS regressions (and logit regressions for columns 3 and 4) of the mental health variables on a dummy for whether the mental health variable is measured at application or in the follow-up survey. The odd columns use fixed effects while the even columns control for the basic set of controls listed in the table. The *DepressionScore* outcome is the score out of 27 as defined in Table A.1 standardized by the distribution of depression scores for the control group at baseline. The *DepressionLikely* outcome is equal to 1 if the depression score is greater than 10.

Table A.6: Follow-Up Mental Health for Non-Treated Students

	Dependent variable:							
	AnxietyLikely		AnxietyScore		PTSLikely		PTSScore	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Follow-Up	−0.000	0.060	−0.029	−0.005	−0.586	−0.623	0.042	0.047
	(0.338)	(0.363)	(0.182)	(0.182)	(0.393)	(0.439)	(0.205)	(0.202)
SemesterSpring2022		0.121		−0.005		1.117^{**}		0.297
		(0.391)		(0.191)		(0.509)		(0.205)
Female		0.261		0.257		−0.115		0.133
		(0.454)		(0.204)		(0.497)		(0.229)
Asian		0.243		0.474		0.509		0.527
		(0.642)		(0.360)		(0.872)		(0.357)
Black		0.969		0.744^{*}		1.681		1.079^{**}
		(0.821)		(0.377)		(1.116)		(0.479)
Hispanic		−0.026		0.262		−0.547		−0.018
		(0.670)		(0.336)		(0.938)		(0.343)
OtherRace		0.621		0.173		−0.219		0.206
		(0.860)		(0.398)		(1.188)		(0.431)
CollegeAge		1.150^{**}		0.666^{***}		−0.356		0.393
		(0.539)		(0.230)		(0.841)		(0.316)
Underclassman		0.077		−0.029		0.900		0.156
		(0.450)		(0.240)		(0.633)		(0.269)
Pell		0.330		−0.085		0.813		0.213
		(0.432)		(0.215)		(0.533)		(0.245)
Transfer		−0.033		0.025		-1.161^{*}		−0.205
		(0.494)		(0.225)		(0.642)		(0.278)
PartTime		0.290		0.334		−0.807		−0.018
		(0.597)		(0.271)		(0.730)		(0.252)
Constant	-0.405^{*}	-2.086^{**}	0.023	-1.020^{**}	-0.934^{***}	-2.135^{*}	−0.042	-1.073^{*}
	(0.239)	(0.998)	(0.125)	(0.478)	(0.255)	(1.193)	(0.114)	(0.544)
Individual Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
Observations	150	148	150	148	156	154	154	152
R^2			0.0002	0.080			0.0003	0.111
Adjusted R^2			−0.007	−0.002			−0.006	0.035
Log Likelihood	−100.952	−94.740			−83.109	−69.317		
Akaike Inf. Crit.	205.904	215.481			170.217	164.634		

*p<0.1; **p<0.05; ***p<0.01

Note: Estimates in each column are from either logit (columns 1-2 and 5-6) or OLS (columns 3-4 and 7-8) regressions of the mental health variables on a dummy for whether the mental health variable is measured at application or in the follow-up survey. The odd columns use fixed effects while the even columns control for the basic set of controls listed in the table. The *AnxietyScore* and *PTSScore* outcomes are the scores out of 21 and 80 as defined in Tables A.2-A.3 standardized by the distribution of anxiety and PTS scores for the control group at baseline. The *AnxietyLikely* outcome is equal to 1 if the anxiety score is greater than 10, and the *PTSLikely* outcome is equal to 1 if the student likely has PTSD under the DSM-5 Diagnostic Rule as defined in Table A.3.

Table A.7: Intention-to-Treat Effects on Short-Term Resilience Domains

	Dependent variable: Short-Term Resilience Domain Scores						
	Collaboration	Composure	Health	Momentum	Reasoning	Tenacity	Vision
Treatment	0.125***	0.162***	0.078***	0.150***	0.148***	0.121***	0.169***
	(0.022)	(0.033)	(0.017)	(0.029)	(0.034)	(0.029)	(0.032)
Treatment×Collaboration	−0.173***						
	(0.030)						
Treatment×Composure		−0.237***					
		(0.044)					
Treatment×Health			−0.133***				
			(0.029)				
Treatment×Momentum				−0.205***			
				(0.039)			
Treatment×Reasoning					−0.227***		
					(0.050)		
Treatment×Tenacity						−0.160***	
						(0.036)	
Treatment×Vision							−0.222***
							(0.043)
Observations	521	521	521	521	521	521	521
R^2	0.856	0.819	0.876	0.837	0.792	0.845	0.819
Adjusted R^2	0.852	0.814	0.872	0.833	0.787	0.841	0.814

*p<0.1; **p<0.05; ***p<0.01

Note: Estimates in each column are from OLS regressions run separately for each domain score (0.2-1) for short-term resilience on a treatment dummy, the baseline domain score (0.2-1), their interaction, a semester dummy, and dummies for whether the student is female, Asian, Black, Hispanic, or another race, younger than 23 years old, a freshman or a sophomore, a Pell recipient, a transfer student, or a part-time student. All regressions use robust standard errors with those reported in parentheses below the estimates.

Table A.8: Intention-to-Treat Effect on Resilience

	Dependent variable:Short-Term Resilience (Standardized by Control Baseline Resiliences)						
	Remove Collaboration	Remove Composure	Remove Health	Remove Momentum	Remove Reasoning	Remove Tenacity	Remove Vision
Treatment	0.042	0.055^{*}	0.046	0.051^{*}	0.055^{**}	0.048^{*}	0.042
	(0.029)	(0.029)	(0.029)	(0.028)	(0.028)	(0.029)	(0.029)
Treatment×Resilience (remove Collaboration)	-0.113^{***}						
	(0.031)						
Treatment×Resilience (remove Composure)		-0.105^{***}					
		(0.030)					
Treatment×Resilience (remove Health)			-0.118^{***}				
			(0.032)				
Treatment×Resilience (remove Momentum)				-0.100^{***}			
				(0.030)			
Treatment×Resilience (remove Reasoning)					-0.122^{***}		
					(0.029)		
Treatment×Resilience (remove Tenacity)						-0.128^{***}	
						(0.032)	
Treatment×Resilience (remove Vision)							-0.122^{***}
							(0.031)
Observations	521	521	521	521	521	521	521
R^2	0.895	0.898	0.896	0.902	0.902	0.892	0.895
Adjusted R^2	0.893	0.895	0.893	0.900	0.900	0.889	0.892

*p<0.1; **p<0.05; ***p<0.01

Note: Estimates in each column are from OLS regressions of short-term resilience on a treatment dummy, baseline resilience, their interaction, a semester dummy, and dummies for whether the student is female, Asian, Black, Hispanic, or another race, younger than 23 years old, a freshman or a sophomore, a Pell recipient, a transfer student, or a part-time student. Different baseline resiliences and short-term resiliences are calculated by removing one domain and each are standardized by the distribution of the baseline resilience with that domain removed for the control group. All regressions use robust standard errors with those reported in parentheses below the estimates.

Table A.9: Follow-Up Balance Test

Variable	Treatment Mean	Control Mean	Treatment Effect†	# Obs.
Female	0.713	0.725	-0.013 (0.08)	138
Asian	0.287	0.333	-0.043 (0.081)	138
Black	0.149	0.098	0.05 (0.06)	138
Hispanic	0.322	0.353	-0.028 (0.083)	138
White	0.138	0.118	0.017 (0.059)	138
Other Race	0.103	0.098	0.004 (0.054)	138
College Age	0.805	0.686	0.122 (0.074)	138
Fresh/Soph	0.494	0.529	-0.032 (0.088)	138
Pell	0.644	0.549	0.095 (0.087)	138
USA	0.698	0.667	0.032 (0.083)	137
FirstGen	0.465	0.51	-0.044 (0.089)	137
Transfer	0.31	0.353	-0.047 (0.082)	138
Part-Time	0.138	0.196	-0.061 (0.064)	138
Toddlers	0.057	0.098	-0.04 (0.046)	138
Older Kids	0.448	0.373	0.076 (0.088)	138
Resilience	0.666	0.633	0.033 (0.023)	138
Depression	0.407	0.4	0.008 (0.088)	136
Anxiety	0.267	0.392	-0.124 (0.082)	137
PTS	0.224	0.26	-0.038 (0.077)	135

Note: Significantly different at the 10(*), 5(**), and 1(***)% level
† Coefficient (standard error in parentheses below) on treatment dummy from OLS regression of row variable on treatment and a dummy for semester

Table A.10: Likelihood of Answering Follow-Up

	Dependent variable: Follow-Up							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.733***	0.767***	0.700***	0.139	0.726***	0.728***	0.772***	−1.180
	(0.192)	(0.199)	(0.211)	(1.133)	(0.274)	(0.251)	(0.245)	(1.828)
SemesterSpring2022		0.274	0.074	0.071	0.076	0.075	0.080	0.119
		(0.216)	(0.226)	(0.226)	(0.227)	(0.227)	(0.227)	(0.362)
Female		0.476**	0.426*	0.426*	0.425*	0.429*	0.427*	0.682*
		(0.212)	(0.223)	(0.223)	(0.223)	(0.223)	(0.223)	(0.372)
Asian		0.118	−0.040	−0.038	−0.043	−0.040	−0.045	−0.166
		(0.331)	(0.344)	(0.344)	(0.344)	(0.344)	(0.345)	(0.503)
Black		0.518	0.466	0.472	0.470	0.471	0.472	0.416
		(0.404)	(0.425)	(0.426)	(0.426)	(0.426)	(0.425)	(0.680)
Hispanic		−0.032	−0.168	−0.157	−0.169	−0.167	−0.175	−0.316
		(0.325)	(0.342)	(0.342)	(0.343)	(0.343)	(0.344)	(0.520)
OtherRace		−0.773*	−0.875*	−0.869*	−0.878*	−0.882*	−0.882*	−0.931
		(0.439)	(0.474)	(0.475)	(0.475)	(0.474)	(0.476)	(0.782)
CollegeAge		−0.353	−0.464	−0.469	−0.468	−0.470	−0.472	−0.952*
		(0.326)	(0.341)	(0.342)	(0.341)	(0.341)	(0.342)	(0.564)
Underclassman		0.031	0.004	0.002	0.005	0.005	0.015	0.157
		(0.218)	(0.230)	(0.230)	(0.230)	(0.231)	(0.232)	(0.380)
Pell		−0.246	−0.185	−0.186	−0.184	−0.188	−0.189	−0.508
		(0.224)	(0.240)	(0.240)	(0.240)	(0.240)	(0.240)	(0.388)
Transfer		−0.281	−0.305	−0.297	−0.308	−0.310	−0.307	−0.441
		(0.277)	(0.289)	(0.290)	(0.292)	(0.291)	(0.290)	(0.469)
PartTime		−0.041	0.027	0.008	0.028	0.023	0.025	0.163
		(0.294)	(0.311)	(0.312)	(0.311)	(0.311)	(0.311)	(0.466)
resilienceIndex			−2.504***	−2.982**	−2.513***	−2.523***	−2.546***	−3.292**
			(0.959)	(1.306)	(0.961)	(0.960)	(0.957)	(1.451)
DepressionLikely			−0.223	−0.223	−0.188	−0.223	−0.223	−0.426
			(0.278)	(0.279)	(0.359)	(0.279)	(0.280)	(0.430)
AnxietyLikely			−0.131	−0.126	−0.132	−0.087	−0.141	−0.093
			(0.293)	(0.295)	(0.294)	(0.368)	(0.295)	(0.424)
PTSLikely			−0.268	−0.263	−0.267	−0.268	−0.106	−0.035
			(0.283)	(0.282)	(0.283)	(0.282)	(0.388)	(0.435)
Treatment×Resilience				0.851				1.511
				(1.676)				(1.994)
Treatment×DepressionLikely					−0.063			0.344
					(0.432)			(0.587)
Treatment×AnxietyLikely						−0.088		−0.008
						(0.460)		(0.599)
Treatment×PTSLikely							−0.278	−0.358
							(0.480)	(0.579)
Constant	−1.135***	−1.046**	1.250	1.559	1.245	1.251	1.245	2.185*
	(0.145)	(0.497)	(0.890)	(1.052)	(0.893)	(0.890)	(0.892)	(1.288)
Observations	521	521	459	459	459	459	459	459
Log Likelihood	−320.100	−311.705	−282.676	−282.546	−282.664	−282.656	−282.501	−280.027
Akaike Inf. Crit.	644.201	649.409	599.351	601.093	601.329	601.313	601.002	624.054

*p<0.1; **p<0.05; ***p<0.01

Note: Estimates are from logit regressions of a follow-up dummy on a treatment dummy and the controls listed.

Table A.11: Intention-to-Treat Effects on Medium-Term Resilience Domains

	Dependent variable:						
	Collaboration	Composure	Health	Momentum	Reasoning	Tenacity	Vision
Treatment	0.091*	0.028	0.068*	0.012	0.022	0.014	0.096**
	(0.051)	(0.045)	(0.035)	(0.044)	(0.040)	(0.042)	(0.044)
Treatment×CollaborationHigh	−0.091						
	(0.074)						
Treatment×ComposureHigh		−0.022					
		(0.063)					
Treatment×HealthHigh			−0.080				
			(0.056)				
Treatment×MomentumHigh				0.031			
				(0.063)			
Treatment×ReasoningHigh					−0.079		
					(0.061)		
Treatment×TenacityHigh						0.003	
						(0.067)	
Treatment×VisionHigh							−0.176***
							(0.058)
Observations	139	139	138	139	139	139	139
R^2	0.345	0.358	0.321	0.309	0.325	0.257	0.321
Adjusted R^2	0.271	0.286	0.244	0.231	0.248	0.174	0.244
Note:							*p<0.1; **p<0.05; ***p<0.01

Note: Estimates in each column are from OLS regressions run separately for each domain score (0.2-1) for medium-term resilience on a treatment dummy, a dummy for whether the domain score at baseline was greater than the median domain score for the control group, their interaction, a semester dummy, and dummies for whether the student is female, Asian, Black, Hispanic, or another race, younger than 23 years old, a freshman or a sophomore, a Pell recipient, a transfer student, or a part-time student. All regressions use robust standard errors with those reported in parentheses below the estimates.

2019

2019/1, Mediavilla, M.; Mancebón, M. J.; Gómez-Sancho, J. M.; Pires Jiménez, L.: "Bilingual education and school choice: a case study of public secondary schools in the Spanish region of Madrid"
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2020

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2021

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2022

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2023

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