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Incidence and Effects of Reported University Student Absences

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Despite the potential for illness or bereavement to significantly disrupt education, there is little evidence about the frequency and impact of absences in higher education. Using administrative data from a large public university in the United States, we analyze the incidence of reported student absences and their effects on grades and retention. We document significant heterogeneity in the use of university-excused absences across gender, race/ethnicity, and income levels. This finding offers insight into how students utilize policies to mitigate the adverse effects of absences. Furthermore, estimates show that these reported absences decreased the likelihood of a student returning the next semester, particularly for first-year students. These effects do not vary across student characteristics. Among students who return to the institution, reported absences lower the same-term GPA but do not affect future GPAs. The same semester effects appear to be larger for students from less advantaged backgrounds. These findings are helpful for policymakers seeking to mitigate both disparities in the use of institutional policies designed to help students and the adverse effects of absences on educational outcomes.

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Incidence and Effects of Reported University Student Absences*

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Abstract: Despite the potential for illness or bereavement to significantly disrupt education, there is little evidence about the frequency and impact of absences in higher education. Using administrative data from a large public university in the United States, we analyze the incidence of reported student absences and their effects on grades and retention. We document significant heterogeneity in the use of university-excused absences across gender, race/ethnicity, and income levels. This finding offers insight into how students utilize policies to mitigate the adverse effects of absences. Furthermore, estimates show that these reported absences decreased the likelihood of a student returning the next semester, particularly for first-year students. These effects do not vary across student characteristics. Among students who return to the institution, reported absences lower the same-term GPA but do not affect future GPAs. The same semester effects appear to be larger for students from less advantaged backgrounds. These findings are helpful for policymakers seeking to mitigate both disparities in the use of institutional policies designed to help students and the adverse effects of absences on educational outcomes.

Keywords: Absences, Higher Education, Student Success

JEL Codes: I21, I23, I10

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I. Introduction

Universities dedicate many resources to improving student success. Consequently, a large body of literature has sought to identify the factors that affect student success and the types of interventions that can help students succeed in college. One factor that administrators and researchers may expect to matter is the occurrence of shocks that affect a student's ability to perform well. This paper provides evidence about a particular type of shock: student absences from courses due to the death of family members (bereavement) and student illnesses. Many institutions acknowledge these challenges and have academic policies addressing these events. In fact, policies on course absences have existed for decades across institutions; Lotz (1954) documents characteristics of these policies across institutions that many faculty will find similar to current policies at their institutions.

Despite this broad acknowledgement of an important issue, there is relatively little empirical research about these potential academic shocks. The primary reason for this dearth of research is the lack of suitable data. Unlike the K-12 system,[1] absences are not a first-order issue, so institutions typically do not track absences, but instead rely on policies that dictate how individual faculty may or may not handle them. Ultimately, this means that the necessary data to investigate external factors such as bereavement and illness are not typically collected or available at scale.

In this study, we use novel, detailed administrative records from a large public university in the United States (henceforth "the University") that allow us to study reported student absences. As described in detail below, we are able to conduct this research due to the University's centralized absence reporting system that tracks both the reason and length of student absences. We combined the

[1] In K-12 systems, attendance can be a first-order problem as truancy laws require schools to monitor student attendance, and states may tie funding to attendance and other academic outcomes that could be affected by it. In fact, chronic absenteeism is increasingly the focus of school districts (Garcia and Weiss, 2018). Studies using the variation in timing of standardized tests have shown that additional days of schooling increase test scores (e.g., Marcotte and Hemelt, 2008; Fitzpatrick, Grissmer and Hastedt, 2011; Aucejo and Romano, 2016; Goodman, 2014) suggesting that lower attendance would decrease test scores.

absence data with administrative student records to provide a longitudinal panel of students by semester. We use the longitudinal structure to answer several questions. First, what is the incidence of these reported absences and how does it vary over time and by student characteristics? Second, using the rich set of data in a regression approach, we ask what effect these absences have on student retention. Finally, for students who are retained, we use an event study design to plausibly identify the effects on student GPA.

We begin by discussing the data and the institutional context of the research. We then discuss how we can interpret the data on *reported* absences. These data likely suffer from measurement error due to non-reporting (students are encouraged but not required to submit absence requests). We argue that our approach will still produce unbiased estimates of reported absences but the point estimates will be biased in terms of the effects of all underlying events (reported and unreported). We attempt to understand more of this reporting issue in two ways. First, there are comparisons of demographic groups for which we would not expect the incidence of underlying events to be different (e.g., male and female for bereavement-related absences). In those cases, disparities in reported absences are due to differences in reporting, which is an important result for researchers and administrators. Second, we provide some benchmark estimates of incidence of events across demographic groups using data from the National Longitudinal Survey of Youth 1997 (NLSY97). We find evidence that male students appear to report fewer absences than female students even when there is no reason to expect differences in underlying incidence of events. We also document that bereavement and illnesses over seven days are more likely to be reported by Black students, students with lower GPA, and students from lower socioeconomic ZIP codes, although we also document that these groups are likely to have a higher incidence of these events.

We start by examining whether these absences affect the likelihood that the student is enrolled at the institution the following semester. Estimates suggest that illnesses that are both short (less than seven days) and long (seven days or more) decreased the likelihood of returning. The effects are particularly large for first-year students for whom bereavement also had negative effects. Among these students, a bereavement absence is associated with a 4.83 percentage point decrease in being enrolled the following semester.

We then use the event study approach of Callaway and Sant'Anna (2021) to estimate the effects on GPA for those students who continue at the university. For bereavement and longer illnesses, we find that students earned a lower term GPA in the semester of the absence and some evidence of a smaller effect the next semester. The bereavement effects are the most pronounced for students who are historically more likely to struggle in higher education. Specifically, Black students, students from the lowest income ZIP codes, and students with the lowest high school GPA respectively experienced a 0.25, 0.18, and 0.17 standard deviation decrease in their grades associated with reported bereavement absences. Finally, these negative effects occur even though the University has policies in place to excuse these absences. This suggests that the policies in place—which are similar to those at many institutions–are not sufficient to eliminate the negative effects.

II. Related Literature

There is a vast literature on student success in college which is too large to summarize here. However, while there is little literature in higher education using longitudinal data to study student absences, there is a set of related research. For example, non-trivial research explores the effect of course attendance on student outcomes, but it typically analyzes endogenous attendance, without examining the underlying reasons for missed classes. In addition, the data used for these studies are usually collected by an individual instructor, and therefore, the effects are estimated within the context of a particular course. Much of this literature is published within the subfield of teaching effectiveness within each academic discipline. Examples in economics include Chen and Lin (2008), Marburger (2006), Stanca (2006), Cohn and Johnson (2006), and Lucey and Grydaki (2023).[2]

Another strand of the literature uses surveys of students to try to understand factors that affect their attendance. These samples are often small convenience samples, involve self-reported measures of course attendance, and frequently use methods to identify correlations in the data. For example, Oldfield et al. (2018) conducted a survey of 618 students at a university in the UK and found evidence that attendance decreased with course deadlines, more hours of paid employment, a lack of sense of belonging, and mental health issues. Similarly, a survey of 224 students in Ireland found that factors such as living on campus and fewer hours of employment are positively associated with course attendance (Kelly, 2012). Again, there are similar studies in the pedagogical literature across academic disciplines (Moores, Birdi and Higson, 2019). Data from larger surveys have also been used to show, for example, that lecture attendance may be affected by personality types (Delaney, Harmon and Ryan, 2013).

Due to the challenges of collecting data, there is relatively little literature that uses longitudinal data—for better identification—to examine the effects of household or health shocks on student success. Using similar data to those used in this paper, Harris and Reynolds (2024) find a small effect of COVID-19-related absences on student performance, although they present evidence that the negative effects might have been mitigated by increased grading leniency during the pandemic. There is evidence that mononucleosis (mono)—a disease which causes severe fatigue that may last several weeks—lowers student success (Macsween et al., 2010). Research suggests that worse mental health is negatively associated with student success (Eisenberg, Golberstein and Hunt, 2009; Cornaglia, Crivellaro and McNally, 2015). Some research suggests that significant household illnesses affect student outcomes during high school and appear to affect college choices (Johnson and Reynolds, 2013). Using national administrative data in Tai-

[2] See Moores, Birdi and Higson (2019) for examples across a variety of disciplines.

wan, Chen, Chen and Liu (2009) find that unexpected maternal deaths decrease the likelihood of enrolling in college by age 18.

III. Data and Institutional Details

For our analysis, we use de-identified administrative records from the University that comply with FERPA and HIPAA requirements. Use of student records is common in education research, but this institution provides information not normally available: data on student absences. The availability of these data is due to how the University handles student course absences. The University largely centralizes the excused absence process by having students report absence requests to the "Dean of Students" office along with any supporting documentation. The office reviews the request and then emails *all* of the student's instructors with a general reason for absence (e.g., illness, bereavement, family emergency) and the length of the absence. Students have an incentive to report "official" absences because doing so allows them to miss class or reschedule homework deadlines and exam dates. Having a centralized system also makes it simpler for students to report absences since they only have to contact one office rather than each instructor. This system is also simpler for faculty who do not need to collect documentation for every absence. As such, if students approach faculty first, the faculty member *may* direct them to report the absence through the appropriate office. Nonetheless, students may choose to work directly with individual faculty members rather than use the centralized system.

This centralization is useful for studying absences for several reasons. First and foremost, the University collects detailed data that can be merged with other student records. Second, centralization creates more uniform—and arguably higher-quality—absence data. Absence data collected from instructors or classes can vary across courses, depending on whether the faculty member collected data, whether they required documentation, and the instructor's approachability. Furthermore, instructors may choose different "allowances" for the same absence. At the University in the study, verification is regularly handled by the same office and all instructors are reminded of the acceptable duration for excused absences, such as bereavement. Finally, this may reduce some of the problems of endogenous reporting. Students in general may be more likely to request an absence in a course where they are struggling, which would create challenges when using course-level absence data. In this case, students report to the University and receive allowances across all courses, mitigating the connection between performance in a particular course and allowed absences across courses.

We use data from the Fall 2015 semester to the Fall 2019 semester in our analysis. We stop prior to the pandemic because of the disruption to the educational environment and substantial grade inflation associated with the University's response to the pandemic (Harris and Reynolds, 2024). We focus the sample on first time in college (FTIC) undergraduate students. We differentiate the absences into three broad categories: bereavement, student illness, and other absences. To further explore mechanisms, in some specifications, we separate illnesses into short-term (less than seven days) and longer-term illnesses (seven days or more).

Beyond the absence data, we also have information about student demographics (e.g., sex, race/ethnicity) and measures of incoming academic ability (high school GPA and ACT/SAT scores), and student outcomes including retention and term GPA. We do not have socioeconomic data for the students, but we do have their home ZIP codes, which we use to obtain socioeconomic information for their local region. Specifically, we use the 5-year American Community Survey (ACS) tabulations for 2015-2019 to calculate the median household income and share of those aged 25+ with at least a four-year degree within each ZIP code.

While these data represent a significant improvement over single-course studies, a downside to the administrative records is that we only have data from one institution. Even though we cannot know whether absence incidence and effects would be similar at other institutions, we can show that the University is comparable to a large number of institutions using data from the Integrated Postsecondary

Education Data System (IPEDS). We collect data on all public universities from 2015-2019 with at least 10,000 students enrolled in 2015. This includes the University as well as 281 other institutions totaling 5,633,294 full-time equivalent (FTE) enrollment, which is approximately 80.8% of all public four-year FTE enrollment and 50.2% of FTE at all four-year institutions. Figure 1 shows that the University falls within the interquartile range of this set of institutions in terms of percentage male, percentage in most racial and ethnic categories, 25th- and 75th-percentile ACT scores, and percentage of students receiving financial aid. The University is at the higher end of the interquartile range for the percentage of white students, and the percentage of students with loans is above the interquartile range. Overall, the University is similar to the institutions that many students in the United States attend.

IV. Reported Absences

A. Reported Absences vs. Events

An important aspect of the data is that it measures *reported* student absences. The incidence of an absence is a combination of the true underlying likelihood of an event happening and the probability that the student reports it to the University. The official and oftentimes documented nature of the absence requests through the Dean of Students Office makes it less likely that absences are overreported (absences claimed for non-existent events). Nonetheless, some students might be more comfortable lying to administration rather than an instructor, which would result in overreporting. The more likely scenario is that official absences are underreported (events occur, but the student does not report to the Dean of Students Office).

Consider a standard selection model where R_{it} is a reported absence for student i at some time t. Since all variables are measured at the same point in time, we will ignore the time subscripts in this discussion. Defining E_i as an indicator for an event and X_i as a set of observable characteristics, we could write the selection into reporting an absence as

$$R_i^* = E_i\delta + X_i\gamma + u_i \tag{1}$$

where R_i^* is an unobserved latent variable. The actual reported absence is

$$R_i = \begin{cases} 1 & \text{if } R_i^* > 0 \\ 0 & \text{if } R_i^* \leq 0 \end{cases} \tag{2}$$

For simplicity, assume that X_i is a set of indicators for different demographic groups. If there is no difference in the likelihood of reporting across groups ($\gamma = 0$) then the difference in the incidence of reported absences across groups is due to the differential likelihood of E happening across groups. However, if there are differences in reporting, R_i will reflect both the differential likelihood of E and the differential likelihood of reporting E.

Importantly, the *reported* absence is a policy-relevant variable for which very little research exists. Faculty and administrators have likely formed estimates of variation in absences across groups based on experience, but differences in those absences have not been formally documented. Providing estimates of the incidence of different types of absences across an entire university is useful. Further exploration of variation in the incidence across student groups is also helpful as a baseline for research. However, interpreting differences can be difficult because it is challenging to separate the likelihood of events from the likelihood of reporting.

For example, suppose that some groups are more likely to report an event because they are more likely to seek assistance. This would lead to some individuals—those who do not report the event—not getting the assistance that they need, which could impact student outcomes. For some groups, there may be little reason to suspect differences in the underlying likelihood of an event happening. For example, we would not expect that males experience more or fewer deaths of family members than female students. In such cases, differential incidence is more likely due to differences in reporting. In other cases, the underlying causes of differences in reported absences will be less clear, but we will attempt to shed some light by analyzing external data sources.

Differential reporting is also a potential issue for estimating treatment effects. First, differential reporting may bias results towards zero, as some control group members are actually treated. Second, while we do not expect widespread cases of false absences due to the official process, *reported* cases may be correlated with other factors. For example, struggling students may be more likely to report an absence because they need the assistance the university policy provides and also be more likely to earn a low GPA. In the empirical specification section, we detail how we use a rich set of controls, including course schedule difficulty, to mitigate concerns that selective reporting significantly biases our results.

If there is still non-random selection into reporting absences, our methodology will provide unbiased estimates of *reported* absences but that will be a selected sample that cannot be fully generalized to all *potential* absences. While we cannot be sure, we do not believe this is entirely driving our effects given the centralized reporting system. A student may be struggling in a single course, but a reported absence applies to *all* courses they are taking.

V. Incidence of Reported Absences

We first document and explore variation in the incidence of *reported* student absences across student characteristics in the data. Figure 2 illustrates official absences at the University over time. As indicated, bereavement is the most common reason students seek an official excused absence, followed by illnesses and other absences. The general upward trend is likely due to changes in reporting behavior rather than an increase in absences or changes in institutional policy (the centralized reporting system existed prior to the start of the sample). In fact, the trend is similar to the increase in student accommodations at another university documented by Barnett and Christian (2026), suggesting more general trends in students requesting and/or institutions providing academic assistance. If we restrict the sample to FTIC undergraduate students in the Fall 2015 cohort (3,890 unique students), such that we could observe them for up to four years before the pandemic, 11.0 percent had at least one absence. Of those who had an absence, 17.8 percent had more than one.[3]

Figure 3 illustrates the average share of students with a bereavement in a semester across student characteristics. As shown, Black individuals are the most likely to have an excused absence for bereavement, and non-citizens are the least likely group. Non-citizens—international students—presumably need to travel further to attend a funeral for a close family member, which might explain their lower use of bereavement-related excused absences. There is a pronounced gender difference, with female students much more likely to report a bereavement absence. There is a negative correlation between a student's cumulative GPA the semester before the absence and the likelihood of using an excused absence for bereavement. One explanation is that students with higher GPAs are more adept at recovering from missed class and do not require the accommodations associated with an officially excused absence.[4]

The variation in reported bereavement absences is interesting and important to document as we analyze how absences affect student outcomes. To what extent can we say this variation is due to differences in reporting behavior or underlying events? The gender gap likely stems from different propensities to go through official channels to report excused absences since the death of a family member is arguably orthogonal to a student's gender. This would imply that male students are not reporting absences, which could lead them not to get the assistance they are eligible to receive, negatively affecting their GPA. Other possible explanations for the gender difference could include differential expectations for caregiving and provision of emotional support (e.g., Schrank et al. (2016)), as well as differential

[3]Only 9 students had more than two absences from Fall 2015 to Fall 2019 from the Fall 2015 cohort of FTIC undergraduate students.

[4]Appendix Figures A1-A3 present the results of basic OLS regressions on the correlates of reported absences. The regression results are largely consistent with the raw incidence described in the main text.

expressions of grief (Stroebe, Stroebe and Schut, 2001). For other groups—such as race/ethnic groups—it is less clear whether the gaps reflect event incidence versus reporting behavior.

We can get some idea about differences in deaths of family members by looking at the National Longitudinal Survey of Youth 1997 (NLSY97). That dataset has a variety of useful measures, including a question in 2002 which asked whether a close family member died in the previous five years.[5] Respondents were aged 17 to 23 in that year, which coincides with the age of college students, and we further restricted the sample to individuals who attended college. This leaves a sample of approximately 3,600 to 3,900 individuals, depending on the responses to specific variables. We report the incidence across groups in Figure 4.[6] Note that this is the incidence across five years, while the University data measure incidence in a particular semester (approximately four months), so the levels are quite different.

As expected, there is no gender difference in deaths of family members, which suggests that differences at the University in bereavement incidence are due to differences in reporting or absence use following a family member's death. The incidence of death in the family is highest for Black respondents,[7] but the relative gap to other racial/ethnic groups in the NLSY97 is substantially smaller than the relative gap in reported bereavement at the University. This would suggest that while Black students may be more likely to experience a death in the family than other students, they appear to be more likely than other groups to *report* it as an absence. There is less evidence of differences across family income or Armed Forces Qualification Test (AFQT) scores in family deaths in the NLSY97 (the highest quartiles tend to have a lower incidence but are typically not statistically significant). At the University, there is some evidence that lower-income and lower-GPA students have a higher incidence of reported bereavements. This would

[5]The NLSY survey question was, "In the last five years, that is since you were [respondent's age five years ago] years old, has a close relative of yours died?"

[6]Please see Table A1 for more detailed information.

[7]This is consistent with Thyden, Schmidt and Osypuk (2020) who also find that Black individuals are more likely to experience the death of close relatives, specifically parents and siblings during college years.

also suggest that much of that difference is due to reporting differences and not differences in underlying incidence. The evidence in the NLSY97 on deaths of close relatives is generally matched by the incidence of a close family member being in the hospital for at least five days, presented in the second column.

In the University data, reported absences for any illness are nearly as common as bereavement-related absences, but might be more endogenous. We might expect that longer illnesses are more like bereavements in that they are more likely to represent exogenous shocks than short illnesses (e.g., feeling ill the day of a test). So we explore the incidence of illness-related absences separated by short-term illnesses (less than seven days) in Figure 5a and long-term illnesses (seven days or more) in Figure 5b. There is more variation across groups in the reported incidence of short-term illnesses than long-term illnesses, consistent with differential reporting patterns. The pattern across groups broadly matches that of bereavement absences with females and Black students more likely to report absences. For long-term illnesses, there remains a gender gap and evidence of decreasing incidence with prior semester GPA.

Interestingly, there is some evidence of gender differences in illnesses in the NLSY97 as reported in Figure 6. Female respondents reported a higher share of illnesses and injuries in 2002 and were more likely to report that they had stayed in a hospital for at least 24 hours between 2003 and 2007. There is little evidence of differences in the rate of hospitalization across racial and ethnic groups, but Black and Hispanic respondents reported fewer illnesses and injuries compared to white students. Hospitalization generally decreases with income but reported illness marginally increases with income and AFQT scores in general.

VI. Extensive Margin Analysis

First, we estimate the likelihood of enrolling in the next semester (extensive margin) following a reported absence. We limit our sample to FTIC students from Fall 2015 to 2019 to abstract away from transfer students whose transfer credits are not included in the data. We use the following specification:

$$(3) \qquad Enrolled\ Next_{it} = \beta_0 + Absence'_{it}\beta_1 + X'_{it}\delta + \gamma_t + \delta_m + \varepsilon_{it}$$

where *Enrolled Next* is an indicator for being enrolled the next semester, *Absence* is a vector including indicators for short- and long-term illness and bereavement,[8] X_{it} is a vector including an indicator for being male, race/ethnicity indicators, age group dummies, ACT score,[9] high school GPA, household income and share who graduated college (based on ZIP code). We specifically do not include term GPA in the regression since we want to know the overall effect of the absence and it is possible that absences influenced term GPA which then influenced retention. We include a control for course schedule difficulty measured by the grades of other students (i.e., leave-one-out) in the courses. We also include fixed effects for age group, major, semester, and cohort. For the main specification, we choose not to include individual fixed effects as this would remove students who only attended a single semester (i.e., first-semester first-year students), who are generally more at risk of attrition.

A. Main Extensive Margin Results

We present the main results for the extensive margin in Figure 7 with point estimates bracketed with 95% confidence intervals. The main results show a statistically significant decrease in the likelihood of enrolling in the following semester for students who report either a short-term (5.90 percentage point decrease) or longer-term illness (8.29 percentage point decrease) from a base of 76.43 percent continued enrollment. The point estimate for the influence of bereavement on enrollment in the next semester is statistically insignificant at conventional levels.

[8]We also control for an illness absence of unspecified length, but do not report the point estimates in the results.

[9]We converted any SAT scores into ACT-equivalent scores for this variable. We only lose 236 observations due to missing ACT/SAT scores.

We also present two robustness specifications in the figure. As shown, the point estimates on the absences generally become statistically insignificant with the inclusion of individual fixed effects or with the inclusion of lagged cumulative GPA as a control. Mechanically, both of these robustness specifications will remove observations for first-semester first-year students who do not return to the university. Theoretically, first-year students may be more susceptible to disruptive absences given their relative lack of experience in higher education. As such, there is often particular concern about first-semester, first-year students in the literature and in higher education.[10] So these two robustness checks may be better identified, but also may be missing the students with the largest negative effects. Consistent with this idea, the point estimates when the sample is restricted to only first-year students are more negative relative to the main sample, consistent with a more pronounced effect. The bereavement coefficient, a 4.83 percentage-point decrease, is statistically significant and economically meaningful in the first-year specification from a base of 73.51 percent retention.

Since the first-year results that include the first semester are more susceptible to omitted variable bias, we assess their sensitivity to selection on unobservable factors using the approach of Diegert, Masten and Poirier (2026). The authors define three parameters which can be used to consider how sensitive the estimated effects of the variable of interest are to omitted variable bias. In particular, we estimate the breakdown point ($\bar{r}_X^{bp}$ in their notation) which is a thought experiment about how much the strict exogeneity assumption can be relaxed before the initial hypothesis is overturned (the coefficient on the variable of interest changes sign). Since the exact amount of selection on unobservable factors is not known, the authors follow a previous literature and derive a parameter $\bar{r}_X$, which measures the amount of selection on unobservables into treatment relative to the amount of known selection of observables.

[10]For example, the University of Michigan recently announced that all grades during the first semester will be pass/fail to improve student outcomes beginning Fall 2027. See https://lsa.umich.edu/lsa/academics/lsa-first-semester-grade-covering-pilot-program.html.

Breakdown points for each of our three treatments (bereavement, short illness, long illness) are presented in Table 1 under different comparisons to the baseline selection on observable characteristics into treatment. For example, the breakdown point for bereavement in the first-year sample is 0.32 when compared to all covariates in the model. This can be roughly interpreted as saying that the coefficient on bereavement would change sign if the amount of selection on unobservables was as large as 0.32 times the known selection on observables from all variables (including the cohort, age and major fixed effects). While this is not impossible, it does not seem plausible that some unobserved factors could produce that much selection into treatment (bereavement). The second row shows the breakpoint compared to all covariates except the fixed effects and the last row compares to only high school GPA and income. The percentages get larger as expected: there is less selection on a subset of observables than all observables so the relative amount of selection on some unobserved factor would be larger. However, the results continue to suggest that it is implausible that there is enough selection on unobserved factors to flip the sign on the treatment effects.

Researchers of persistence and retention will note that these are large effects. There is a vast literature attempting to study the factors that affect retention/persistence and these would be considered to be significant magnitudes. Another way to provide some context is to compare to the magnitudes of possible interventions designed to improve outcomes. Bettinger (2004) and Dynarski (2003) find that \$1,000 (nominal) dollars—roughly \$1,500 to \$2,000 in 2026 dollars—in extra financial aid raises retention by about 3 percentage points, while Bettinger and Baker (2014) find that an intensive college coaching program, which cost approximately the same, increased retention by 5 percentage points. Beyond the importance for students—given the returns to a college degree—retention has a large impact on university revenues through both tuition and appropriations. Each additional semester that a student persists is revenue that the university would keep and would outweigh these interventions.[11]

B. Extensive Margin Heterogeneity Analysis

In addition to the main extensive margin results, we also conducted heterogeneity analyses to identify any differential effects for various subgroups. Figures 8 and 9 illustrate the heterogeneity analysis using interaction terms for the various subgroups.[12] Overall, there is little evidence of differential effects of reported absences across the subgroups. Across bereavement, short-term illness, and long-term illness, there are only two statistically significant differential effects. Specifically, the negative effect for reported short-term illness absences is larger for white students than Black students, and the negative effects of reported long-term illness absences are concentrated among students with the lowest tercile of high school GPA. The latter differential effect could result from better prepared students, proxied for by high school GPA, being more resilient to significant absences. Another possible explanation is that students with the lowest high school GPA were the most vulnerable to attrition.[13]

VII. Intensive Margin Analysis

In addition to the extensive margin, we are also interested in any impacts for students who continue at the University. We use an event study approach to see the effects of reported absences on our primary outcome of interest, standardized term grade point average (GPA). The main specification is:

[11] The average net tuition and fees revenue per student plus state appropriations per student during the sample was around \$14,000 a year or the equivalent of approximately \$19,000 in 2026 dollars.

[12] In Appendix Figure A4, we also present stratification heterogeneity analysis. The stratification analysis is largely consistent with the interaction analysis presented in the main text. Nonetheless, there are some differences including a less clear relationship between income and college education and the impact of bereavement.

[13] Appendix Figure A5 presents the heterogeneity analysis for first-semester first-year students. Some main results include that reported bereavement absences are less harmful for those from areas with high college graduation rates, long-term illness is more detrimental for female students, and once again, that students from the top tercile of high school GPA are less affected by long-term illness.

$$Y_{it} = \sum_k \eta_k \mathbb{I}(t - E_i = k) + \theta_1 X_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \tag{4}$$

where Y_{it} is student i's semester standardized GPA (mean zero with standard deviation equal to one) for term t, E_i is the semester in which individual i reported an absence, and $\mathbb{I}(t-E_i = k)$ is an indicator for being k semesters from the specific type of reported absence (e.g., bereavement). Failure to reject the hypothesis that $\eta_k = 0\ \forall k < 0$ offers support for the parallel trends assumption. X_{it} is a vector of time-varying covariates, including course schedule difficulty and other excused absences (e.g., bereavement, illness, family emergency). For example, when we analyze bereavement, we control for the effects of short- and long-term illnesses. Fixed effects for individuals and term-years are denoted by α_i and γ_t, respectively. The primary identification assumption in our approach is that the outcomes of students with a reported absence would have trended the same way as those of students without a reported absence (i.e., parallel trends). The individual fixed effects assist here because they capture any time-invariant characteristics of the students. While fixed effects are helpful, they are unable to control for time-varying effects such as changes in academic performance associated with a family member's declining health.

We specifically estimate the intensive margin effects on those students *who do not attrit*. In other words, we estimate a balanced panel within each cohort for the intensive margin analysis. Since the treatment timing is staggered, we estimate the event study following Callaway and Sant'Anna (2021), focusing on individuals with a single occurrence and using never-treated observations as the control group.[14]

[14]To avoid confounding the event study results with the impact of multiple bereavement-related absences, we exclude the 92 students with more than one occurrence.

A. Main Intensive Margin Results

Figure 10 presents the results of an event study of bereavement absences on standardized term GPA using the approach in Callaway and Sant'Anna (2021). Time $t = 0$ represents the semester in which a bereavement absence occurred. Point estimates are provided with both 90 and 95 percent confidence intervals. As shown, there is evidence supporting the parallel trends assumption based on the point estimates in the pre-treatment period, and there is a modest decrease in standardized term GPA both in the semester of bereavement (0.11 standard deviation decrease) and in the semester directly following the loss (0.09 standard deviation decrease).[15]

Figures 11a and 11b show the event study estimation for short-term and longer-term illnesses.[16] There is no evidence of an adverse effect of shorter illnesses on same-term GPA or following semester GPA. Longer illnesses, however, are associated with decreases in same-term GPA of 0.33 standard deviations. The point estimate in the following semester is also negative but not statistically significant at conventional levels.[17] How should we interpret these results? On the one hand, we would expect that longer illnesses would have more significant effects on students as they would miss more classes and get further behind on coursework. The finding that shorter illnesses have no statistically significant effect may suggest either that they are not long enough to cause significant academic problems or that University absence policies are sufficient to handle short-term illnesses but not longer-term illnesses. Note also that the effects of longer illnesses are larger

[15]Note that the estimates for coefficients further from $t = 0$ are identified with fewer observations, which may affect precision. These estimates should therefore be interpreted with caution. For example, the sample used to identify the $t = -7$ coefficient consists of those who experience a bereavement in their 7th semester at the university. Similarly, the sample at $t = 7$ consists of those students who had a bereavement 7 semesters earlier which would typically be seniors in their spring semester who experienced a bereavement in their first semester at the University.

[16]Similar to the above analysis, we exclude observations with multiple illness-related absences.

[17]Some illness absences do not have a length of time specified, so we do not include this category in our primary estimation. Nonetheless, we present the results in Appendix Figure A7, which shows effects more similar to longer illnesses. This could be because the "unknown" length absences are actually serious but ongoing situations where the University did not record a length of absence. Since we are unsure how to interpret these absences, we do not present estimates in the main text.

than those of bereavement.[18]

It may be worth noting that while bereavement and longer illnesses have negative effects on persistence and same-term GPA, short-term illnesses only appear to have negative effects on the extensive margin. Recall that the GPA estimates are only on the sample that persisted, implying that students who are more heavily affected by these illnesses do not continue and therefore are not part of the GPA analysis. Nonetheless, the same argument could be made for bereavement and longer-term illness, which have impacts on both margins. Another possibility is that shorter illnesses are simply more endogenous than the other absence types, so students who are less likely to persist are more likely to have these shorter illnesses.

B. Intensive Margin Heterogeneity Analysis

To explore heterogeneity across student populations, we estimate a simple two-way fixed effects (TWFE) model that replaces the set of $\mathbb{I}(t - E_i = k)$ indicators with a single indicator for having an absence in that semester—roughly equivalent to the treatment effect at time $t = 0$ in the event study.[19] In this case, we can include interactions of the treatment indicator with an indicator for group membership. This approach allows for a formal test of the statistical significance of treatment effects across groups but relies on stronger identifying assumptions.

Figure 12 presents the results of the heterogeneity analysis for bereavement absences. As shown, there is no differential effect based on gender, but the results indicate that Black students are the most negatively impacted by a bereavement absence. This result indicates that the effect of a reported bereavement absence on same-term GPA is 0.21 standard deviations more negative for Black students

[18]In Appendix Figure A8, we present TWFE results for alternative dependent variables including earning a grade below C or withdrawing from a course. The results indicate that long-term illness absences significantly increase the likelihood of withdrawing from a course and earning a below-C grade in at least one course. Bereavement also increases the likelihood of earning a below-C grade that is marginally significant at the 10-percent level.

[19]A switch to this method does not substantially affect the estimates with negative effects for bereavement and larger negative effects for longer illnesses. However, the effects of shorter illnesses are now marginally statistically significant (see Appendix Figure A9).

than for white students. This effect is unlikely to be driven by selected reporting of “severe” cases (e.g., close family relation). We previously showed that the underlying incidence of family deaths in the NLSY97 is higher for Black students and the reported incidence at the University is substantially higher for Black students. Instead, this negative effect is likely evidence that Black students—who are more likely to experience a bereavement in the first place—are more negatively impacted by bereavements. This could be because on average these students are more at risk in higher education and this type of shock disrupts them more.

The figure further shows that individuals from areas with higher shares of college graduates and higher household incomes are not as negatively impacted by reported bereavement absences compared to those in the lowest terciles (who experience statistically significant standard deviation declines of 0.15 and 0.18). One potential explanation for this finding is that more affluent families are better prepared to handle the financial burden of a family member passing away. For example, a student from a lower-income household might experience greater stress following the death of a family member if the household is financially unprepared for the costs of the funeral and potential lost income from the death of a breadwinner or added expenses of childcare. In some circumstances, students might need to take on extra work to supplement lost income due to a family member’s passing. Financial strain from unexpected travel expenses might be another channel through which lower-income students are differentially impacted. Similar to the extensive margin results, individuals in the lowest tercile of high school GPA are more affected by the absence with a 0.17 standard deviation decline in same-term GPA. The pattern across these results is that bereavement appears to have larger effects on students who are already statistically less likely to succeed in college.[20]

[20] Appendix Figure A10 shows the results for stratification analysis using CSDID, which is largely consistent with the interaction analysis from the TWFE models.

Consistent with the prior estimates, there is little evidence of negative effects for illnesses less than seven days, nor is there significant evidence of heterogeneity across groups (Figure 13a). Estimated effects for illnesses over seven days (Figure 13b) appear to be somewhere between the estimates for short illnesses and bereavement. Female students experience a clear negative effect from a reported long-term illness on same-term GPA and the interaction term is negative with a marginally statistically significant result at the 10-percent level, suggesting that males are more negatively impacted by long-term illness. White students now show a statistically significant negative effect and the interaction term for Black students suggests that they have even larger negative effects (0.52 standard deviation larger negative effect than white students). The differential effects across ZIP code income, ZIP code education and high school GPA do not provide strong evidence of heterogeneous effects.[21]

VIII. Conclusion

Student retention and success are of critical importance to institutions of higher education in the United States. While most researchers, administrators and policymakers would expect that negative shocks such as a family member's death or an illness would negatively affect student success, there is limited existing research on both the incidence of these shocks and their effects on student performance. A key challenge is that data necessary to analyze these events are difficult to collect.

We use panel data from a large public university that collects absences through a centralized reporting system. This means that we have student records about courses and grades over time but also background information from application data and absences from the centralized system. We find evidence that male students underreport bereavement compared to female students, which might suggest underreporting of other absences (e.g., illness). We also find that Black students and those from lower socioeconomic ZIP codes are more likely to report

[21] The pattern for illnesses using TWFE is generally similar to the estimates using stratified samples and the CSDID approach (see Appendix Figure A11 and Appendix Figure A12).

absences.

Our estimates suggest that these reported absences substantially lower the likelihood of a first-year student returning for the next semester. Importantly, we also find no statistically significant differential effects across student populations. Among students who return to the institution, our event study estimates show that reported bereavement and long illness absences lower same-semester GPA and possibly next-semester GPA as well. These results show more heterogeneity and appear to be concentrated among students who come from lower-income ZIP codes and those with lower high school grades.

Importantly, these effects exist even though the University is collecting absence data centrally to help students and faculty address these events. The persistence of adverse outcomes despite existing accommodations suggests that current accommodations—which are similar to those at other institutions—do not fully offset the academic consequences of these shocks. However, it is possible that the centralized system is an improvement over other institutions' practices and therefore effects could be larger at other institutions. For example, an institution with a centralized system might be able to make targeted follow-ups with affected students and direct them to specific resources, whereas other institutions can only provide resources and generally advertise them to students. Or perhaps the University of Michigan is on the right track and all first-semester courses should be pass/fail. More research—and therefore more data collection—is needed to check the incidence and effects across a wider set of institutions. Doing so would allow researchers to begin to examine how differences in university policies may mitigate the negative effects.

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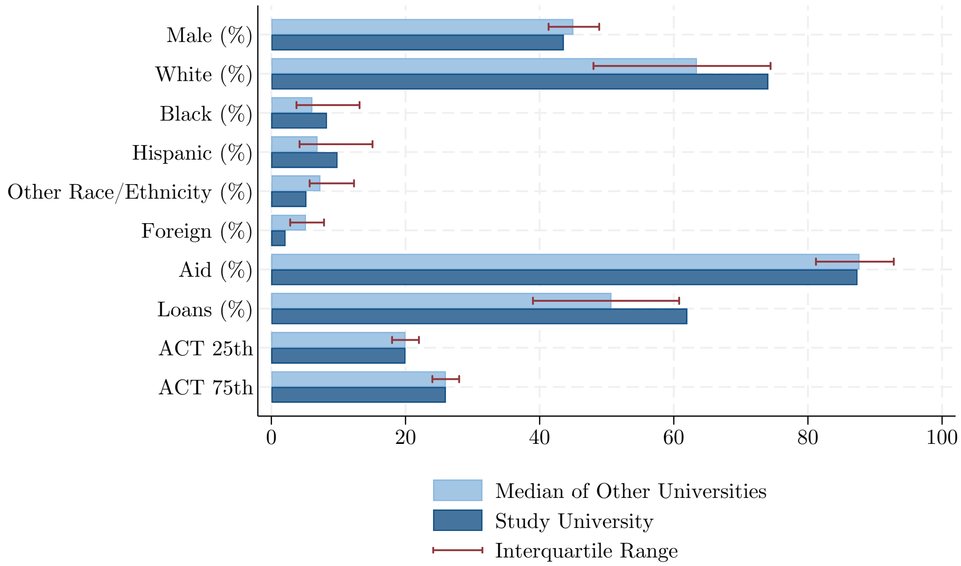
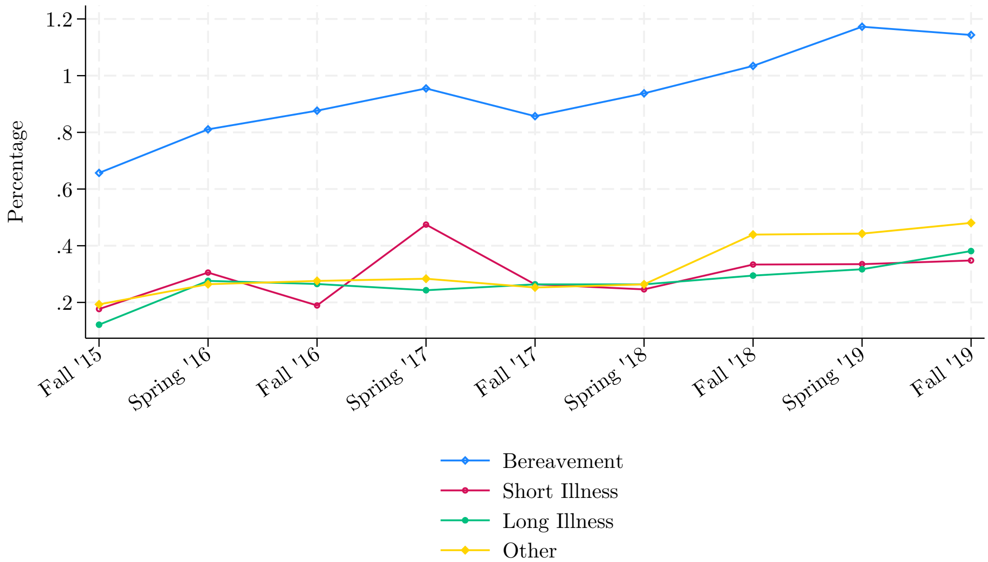
Figure 1. Characteristics of the University



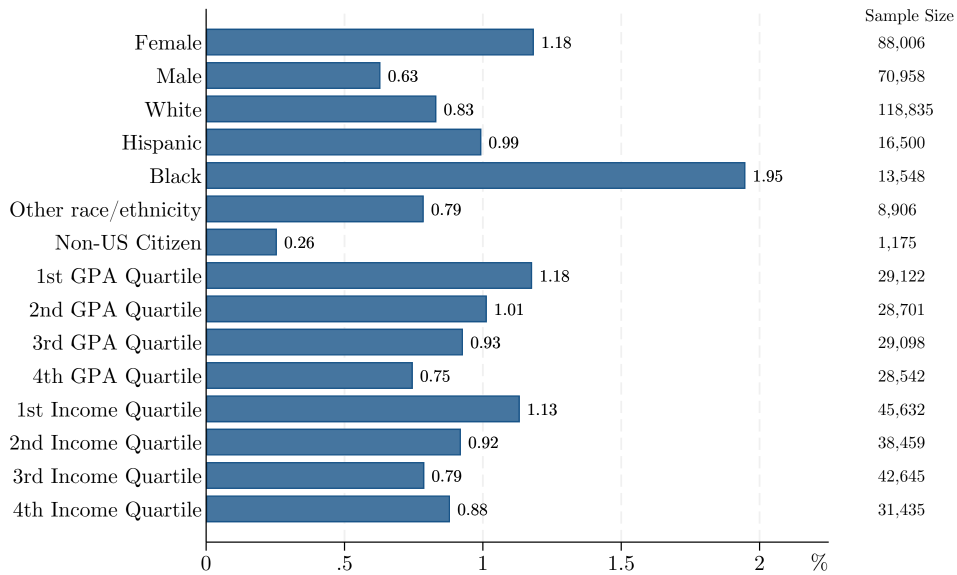
Note: The sample includes 282 public universities in the United States with enrollment over 10,000 students. All calculations are from IPEDS.

Figure 2. Absences



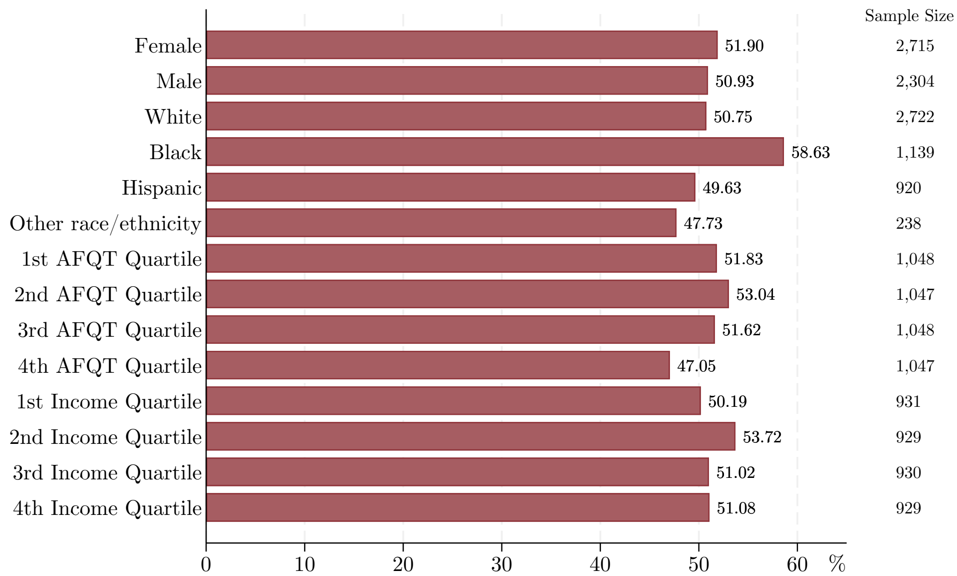
Note: The sample includes undergraduate students at a large public university. Other missed days are for reasons such as family emergencies, court appearances, or military service.

Figure 3. Share of Students with a Reported Bereavement Absence per Semester



Note: The sample includes undergraduate students at a large public university from Fall 2015 to Fall 2019 excluding summer semesters. The GPA quartiles are based on the student's cumulative GPA the semester *before* the excused absence in an attempt to mitigate concerns that the absence caused a lower GPA.

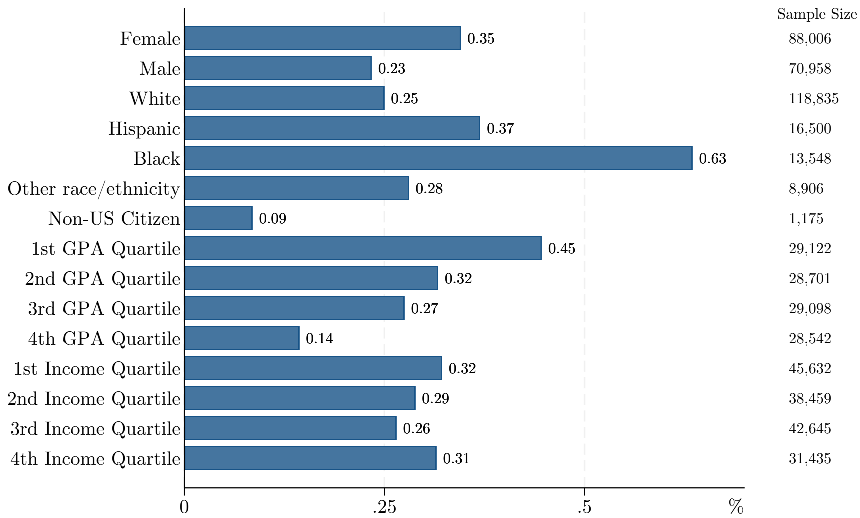
Figure 4. Share of Students with a Close Death within 5 years, NLSY97 Data



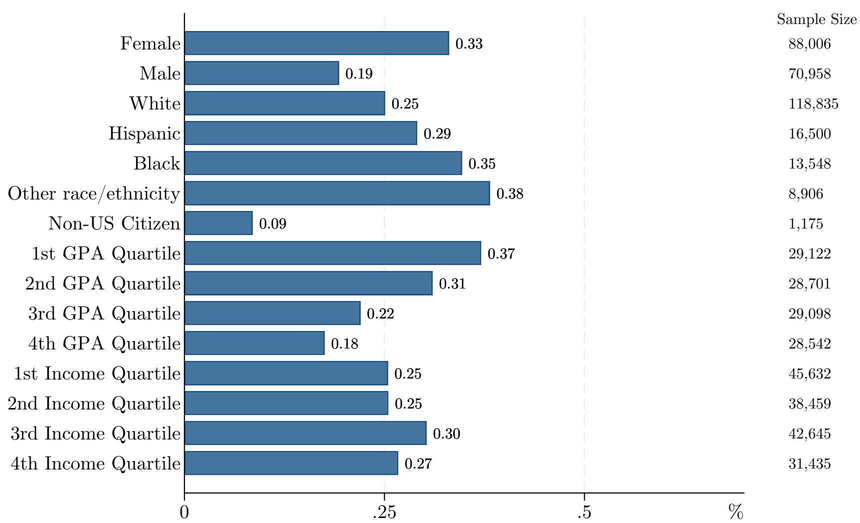
Note: The figure shows the shares of individuals who answered in the affirmative to the following 2002 question: "In the last five years, that is since you were [respondent's age 5 years ago] years old, has a close relative of yours died?" The sample includes individuals aged 17-23 who attended college in the NLSY97.

Figure 5. Share of Students with a Reported Illness Absence per Semester

(a) Short-term Illness (< 7 days)



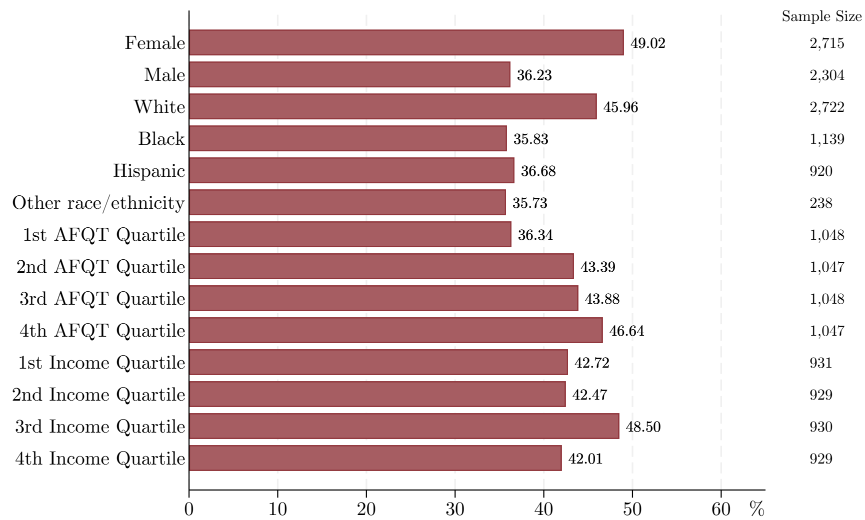
(b) Long-term Illness (≥7 days)



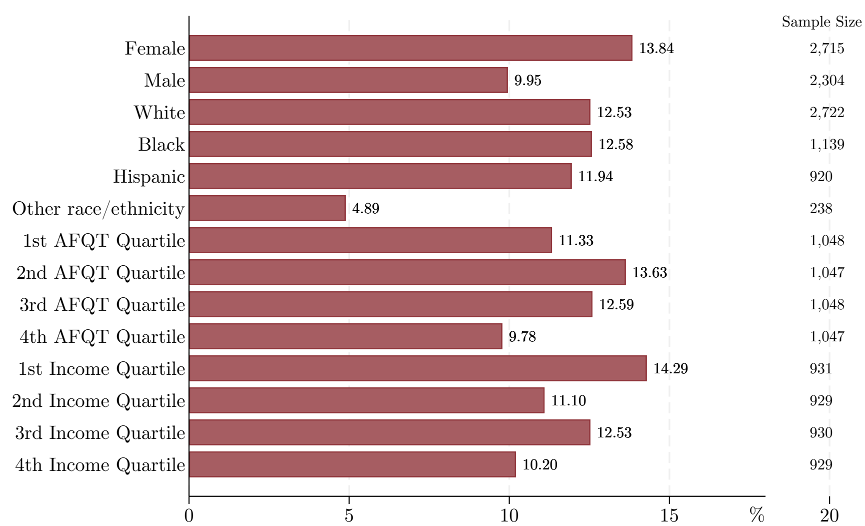
Note: The sample includes undergraduate students at a large public university from Fall 2015 to Fall 2019 excluding summer semesters.

Figure 6. Share treated for an Injury/Illness and Share Hospitalized, NLSY97 Data

(a) Treated for Illness/Injury

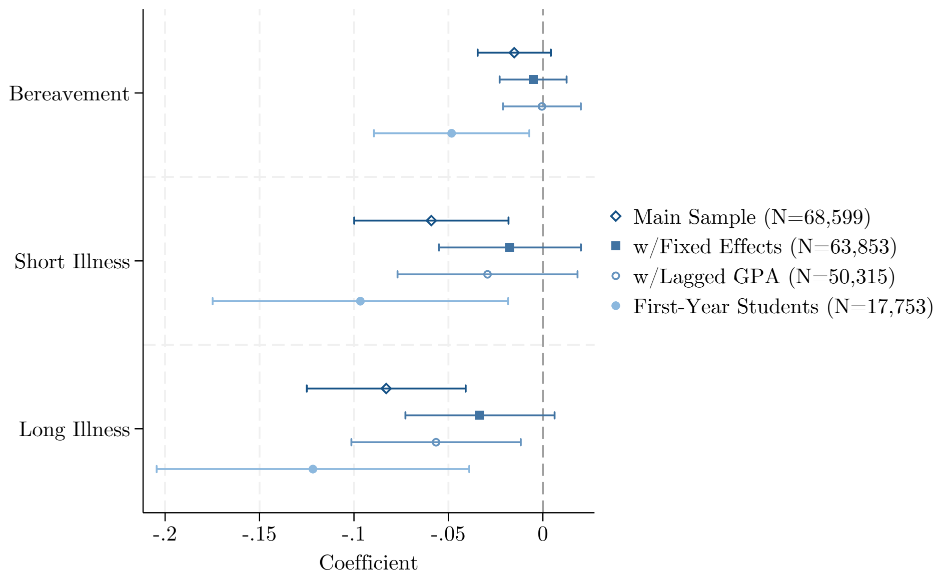


(b) Hospitalized



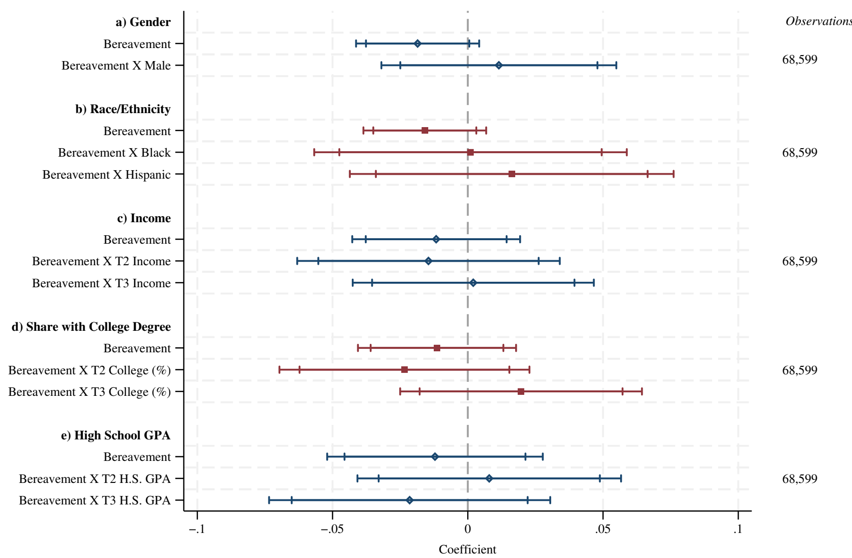
Note: The sample includes individuals aged 17-23 who attended college in the NLSY97. Panel (a) illustrates the share of individuals who received treatment from a doctor/nurse for an injury or illness in the last year. Panel (b) shows the share that were hospitalized for at least 24 hours in the last five years.

Figure 7. Extensive Margin Analysis, Dependent Variable: Enrolled the next semester



Note: The sample includes FTIC undergraduate students at a large public university from Fall 2015 to Fall 2019 for observations where they attended for less than 8 semesters. The first-year sample analyzes the likelihood that first-year students continue into their second semester using the fall 2015-2019 cohorts. Point estimates are provided with 95% confidence intervals and robust standard errors are clustered at the individual level.

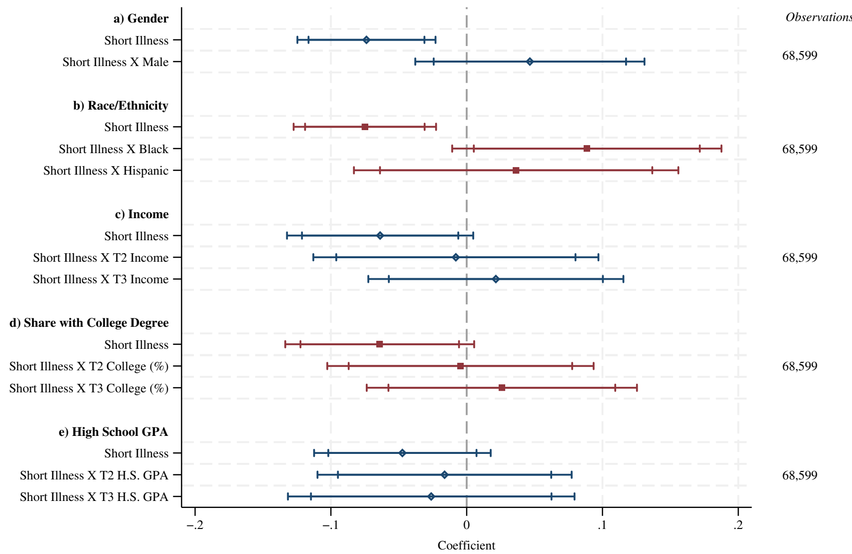
Figure 8. Extensive Margin Interaction Analysis, Dependent Variable: Enrolled the Next Semester, Treatment: Bereavement Absence



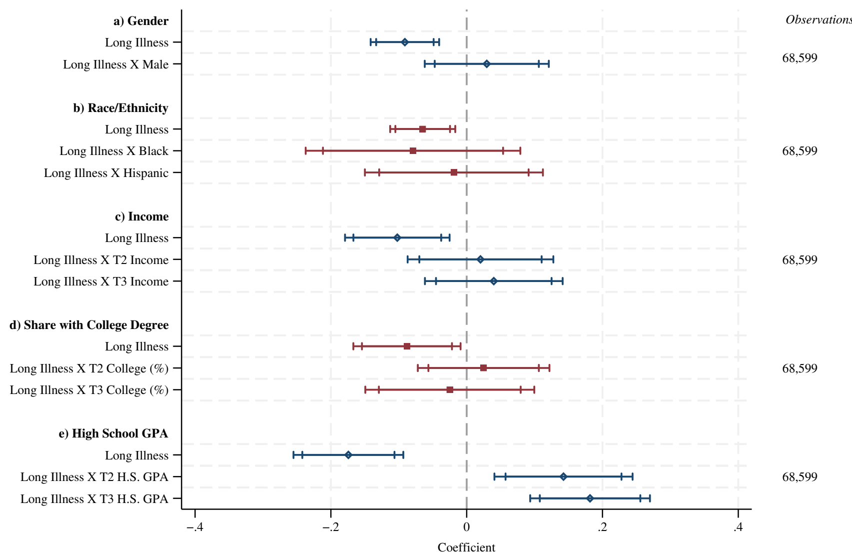
Note: The sample includes FTIC undergraduate students at a large public university from Fall 2015 to Fall 2019 for observations where they attended for less than 8 semesters. Point estimates are provided with 95% confidence intervals.

Figure 9. Extensive Margin Interaction Analysis, Dependent Variable: Enrolled the Next Semester, Treatment: Illness

(a) Short-term Illness (< 7 days)

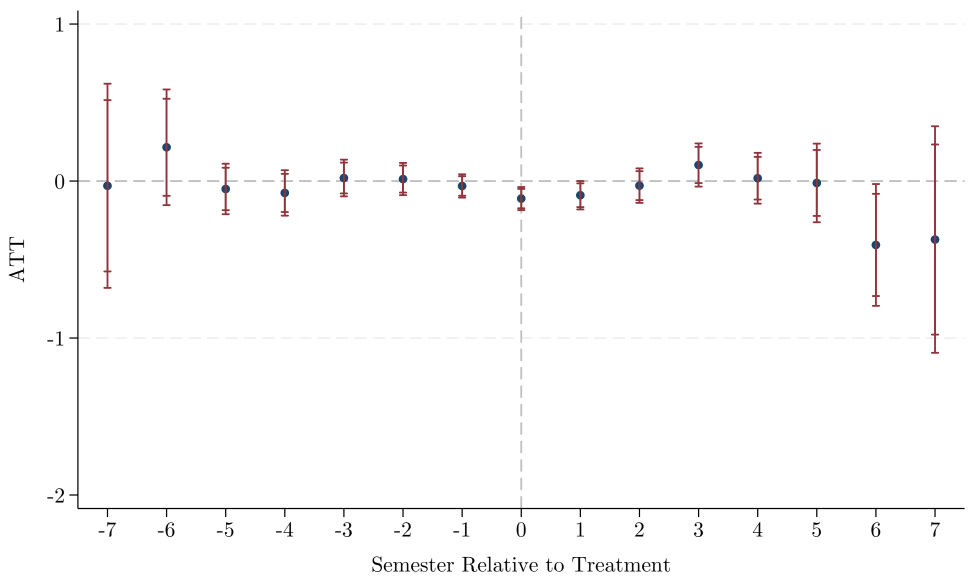


(b) Long-term Illness (≥7 days)



Note: The sample includes FTIC undergraduate students at a large public university from Fall 2015 to Fall 2019 for observations where they attended for less than 8 semesters. Point estimates are provided with 95% confidence intervals.

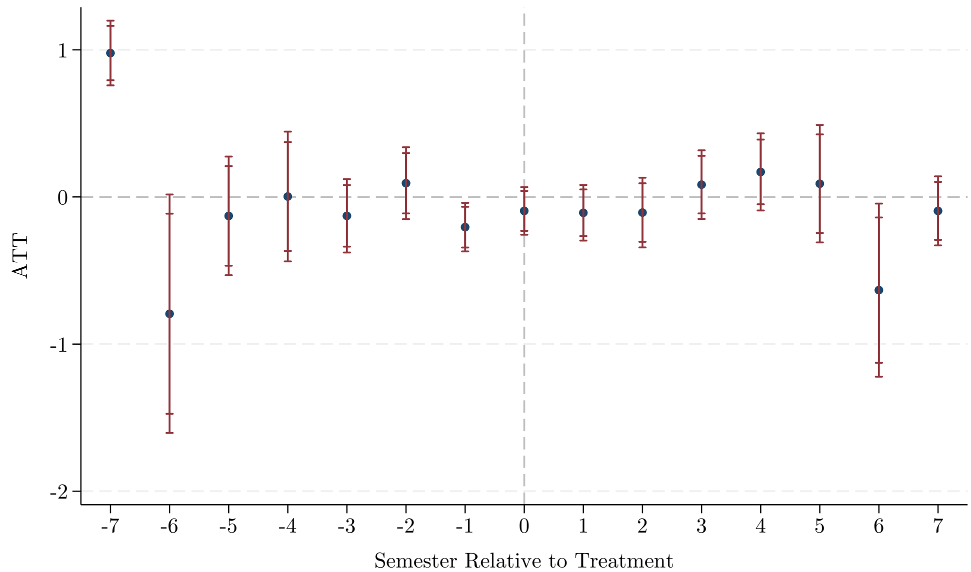
Figure 10. CSDID Estimates of the Impact of Reported Bereavement on Standardized Term GPA



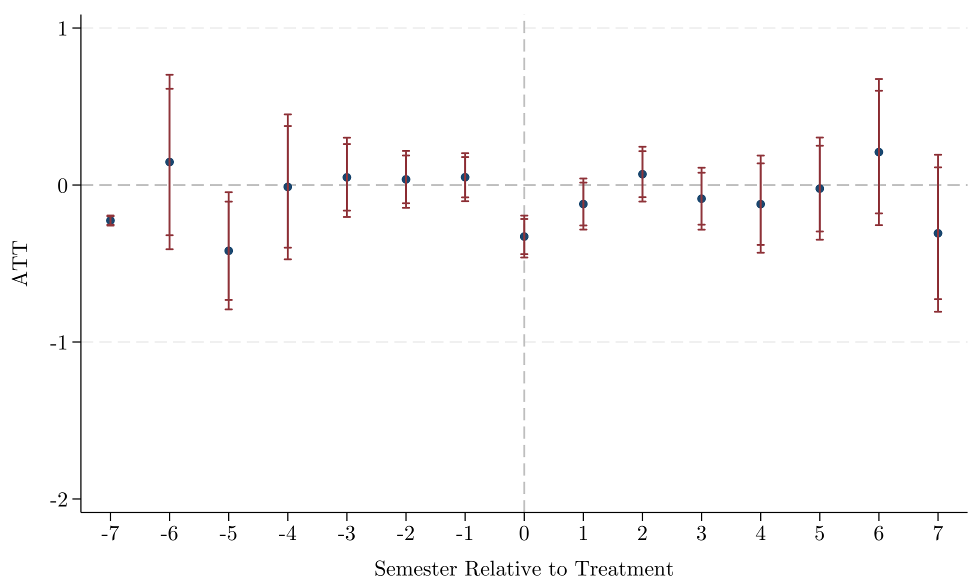
Note: The sample includes FTIC undergraduate students at a large public university from Fall 2015 to Fall 2019 excluding summer semesters who were enrolled throughout the sample period (or graduated for the Fall 2015 cohort). The sample excludes students with multiple absences of the same type. Point estimates are provided with 95% confidence intervals and there were 54,217 observations.

Figure 11. CSDID Estimates of the Impact of Reported Illness on Standardized Term GPA

(a) Short-term Illness (< 7 days)

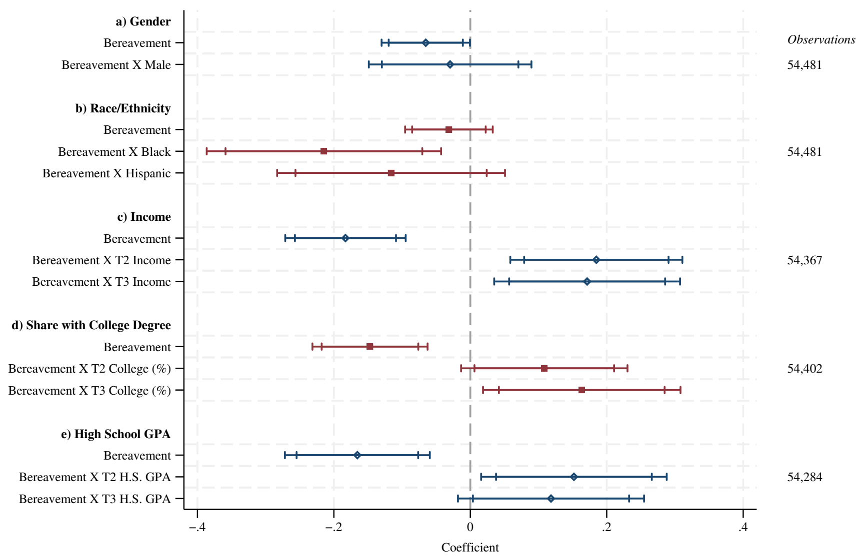


(b) Long-term Illness (≥7 days)



Note: The sample includes FTIC undergraduate students at a large public university from Fall 2015 to Fall 2019 for observations where they attended for less than 8 semesters. Point estimates are provided with 95% confidence intervals and there were 54,746 observations.

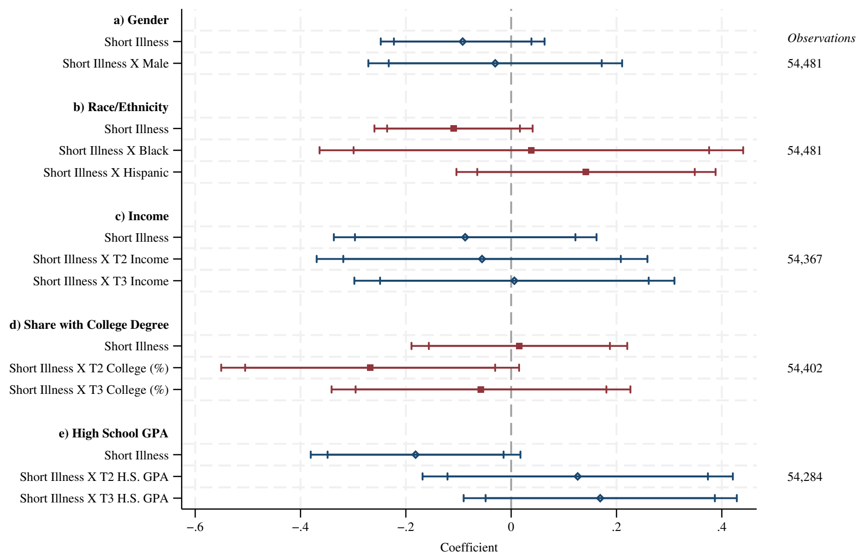
Figure 12. Heterogeneity Interaction Analysis: The Impact of Reported Bereavement on Same-Term Standardized GPA



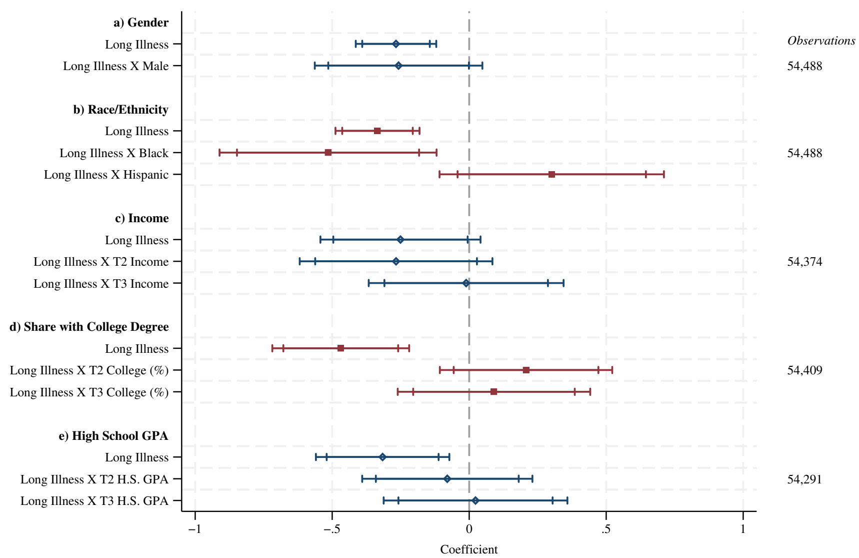
Note: The sample includes FTIC undergraduate students at a large public university from Fall 2015 to Fall 2019 excluding summer semesters who were enrolled throughout the sample period (or graduated for the Fall 2015 cohort). The sample excludes students with multiple absences of the same type. Point estimates are provided with 95% and 90% confidence intervals and standard errors are clustered at the individual level.

Figure 13. Heterogeneity Interaction Analysis: The Impact of Reported Illness on Same-Term Standardized GPA

(a) Short-term Illness (< 7 days)



(b) Long-term Illness (≥7 days)



Note: The sample includes FTIC undergraduate students at a large public university from Fall 2015 to Fall 2019 excluding summer semesters who were enrolled throughout the sample period (or graduated for the Fall 2015 cohort). The sample excludes students with multiple absences of the same type. Point estimates are provided with 95% and 90% confidence intervals and standard errors are clustered at the individual level.

Table 1—Breakdown Points from Sensitivity Analyses of Diegert, Masten and Poirier (2026) for the Extensive Margin Estimates for First-year Students

Group	Bereavement	Short Illness	Long Illness
Relative to all covariates	0.32	0.42	0.42
Relative to main covariates	0.45	0.55	0.68
Relative to HS GPA and income	0.91	0.73	0.85

Note: Each cell shows the breakdown point from Diegert, Masten and Poirier (2026) which is the amount of selection into treatment on unobservable characteristics to flip the sign on the treatment effect, measured as a ratio to the selection into treatment based observable factors. Each column shows the results for a different absence. Each row uses a different set of covariates to serve as the baseline selection on observables used as a reference.

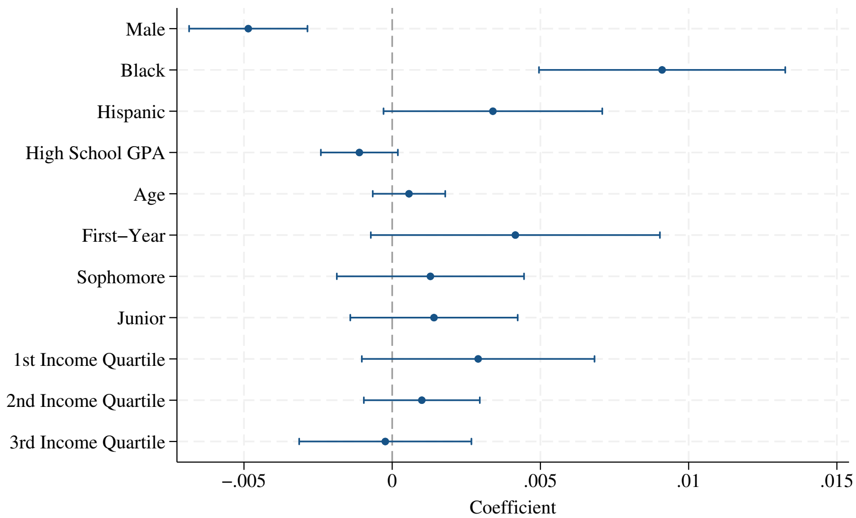
Appendix A

Table A1—Incidence Data in National Longitudinal Survey of Youth 1997

Group	Close death	HH member hosp.	Self hosp.	Num. illness or injury
Male (base)	50.9	16	10	1.51
Female	51.9	16.9	13.8***	2.38***
N	4655	4656	4324	4589
White (base)	50.7	15.5	12.5	2.15
Black	58.6***	19.6**	12.6	1.47***
Hispanic	49.6	16.3	11.9	1.64***
Other	47.7	21.4***	4.9***	1.63***
N	4655	4656	4324	4589
Income quartile 1 (base)	51.3	18.4	15.5	1.81
Income quartile 2	52.4	17.4	11.2**	1.92
Income quartile 3	52.1	16.8	12.1*	1.98
Income quartile 4	50.8	14.4*	10.9**	2.1**
N	3480	3481	3246	3446
AFQT quartile 1 (base)	50.8	14.4	11.3	1.31
AFQT quartile 2	53.0	15.4	12.6	1.89***
AFQT quartile 3	53.7	17.8	12.8	2.04***
AFQT quartile 4	47.4	14.9	10.7	2.08***
N	3924	3925	3657	3880

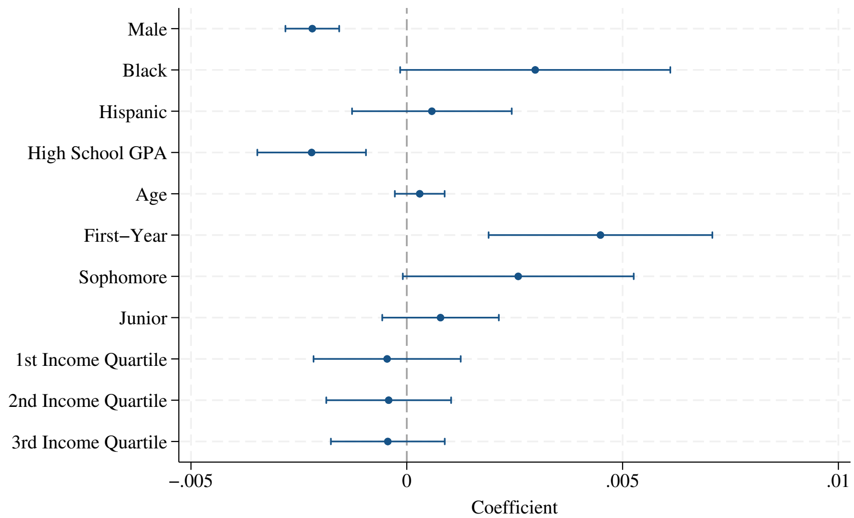
Note: The sample is from the National Longitudinal Survey of Youth restricted to those individuals who attended college. Averages are calculated using sampling weights. "Close death" measures whether someone close died in prior 5 years (2002). "HH member hosp." is whether a household member was hospitalized for at least a week in prior 5 years (2002). "Self hosp." is whether the respondent was in the hospital for at least 24 hours in prior 5 years (2007). "Num. illness or injury" is the sum of 1) the number of times in previous year the respondent received treatment from a doctor/nurse for an injury or illness and 2) the number of times an illness or injury disrupted work/school for at least 24 hours but was not treated.

Figure A1. Correlates with Reported Bereavement, OLS



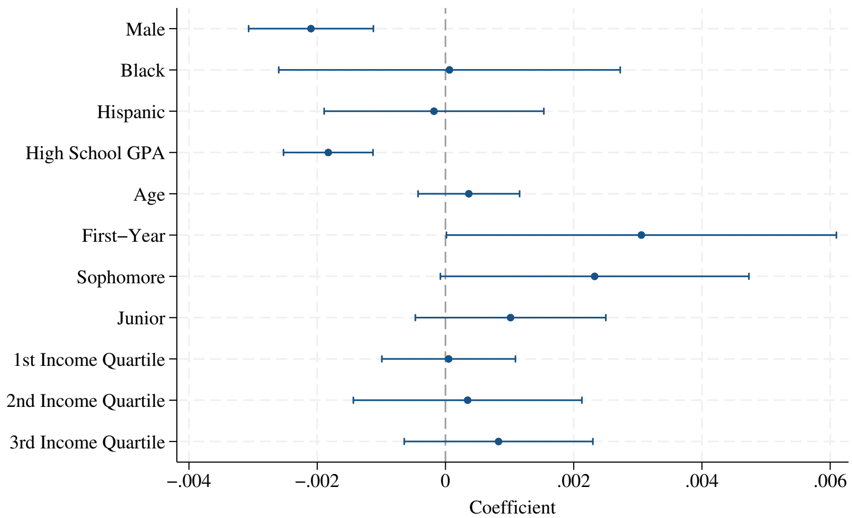
Note: The figure shows the results of a regression with 71,847 observations from FTIC undergraduate students from Fall 2015 to Fall 2019 including the controls shown as well as additional controls for major fixed effects and indicators for non-citizen status and other race/ethnicity. The horizontal bars represent 95 percent confidence intervals and standard errors were clustered at the student and semester/year levels.

Figure A2. Correlates with Reported Short-term Illness (<7 days), OLS



Note: The figure shows the results of a regression with 71,847 observations from FTIC undergraduate students from Fall 2015 to Fall 2019 including the controls shown as well as additional controls for major fixed effects and indicators for non-citizen status and other race/ethnicity. The horizontal bars represent 95 percent confidence intervals and standard errors were clustered at the student and semester/year levels.

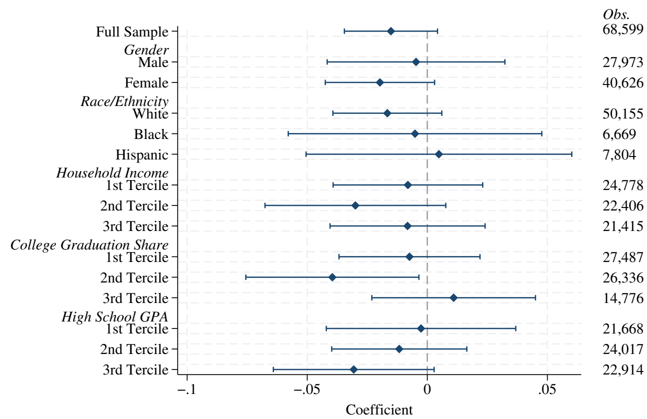
Figure A3. Correlates with Reported Long-term Illness (≥7 days), OLS



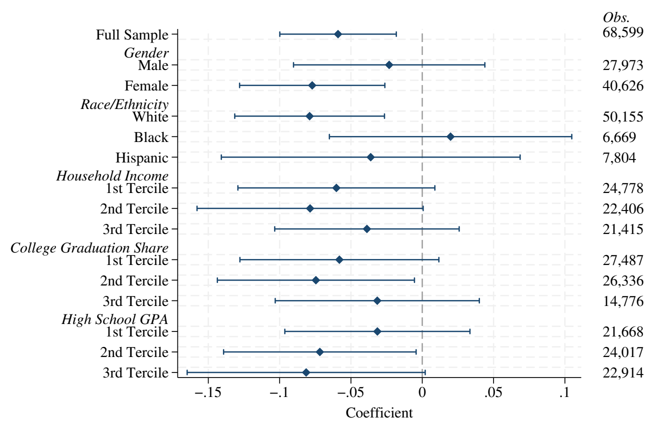
Note: The figure shows the results of a regression with 71,847 observations from FTIC undergraduate students from Fall 2015 to Fall 2019 including the controls shown as well as additional controls for major fixed effects and indicators for non-citizen status and other race/ethnicity. The horizontal bars represent 95 percent confidence intervals and standard errors were clustered at the student and semester/year levels.

Figure A4. Extensive Margin Stratification Analysis, Dependent Variable: Enrolled the Next Semester

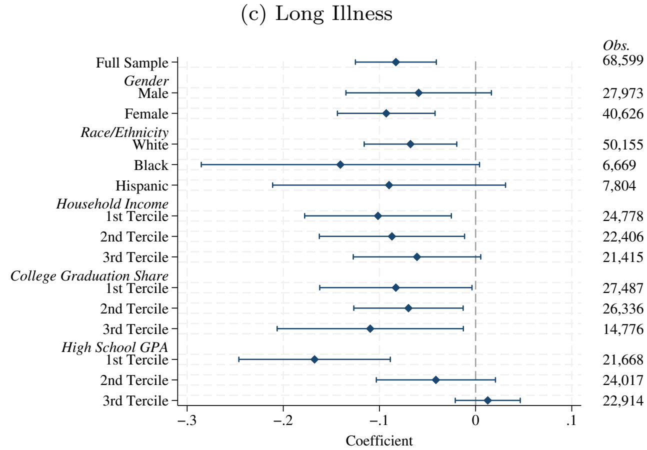
(a) Bereavement



(b) Short Illness



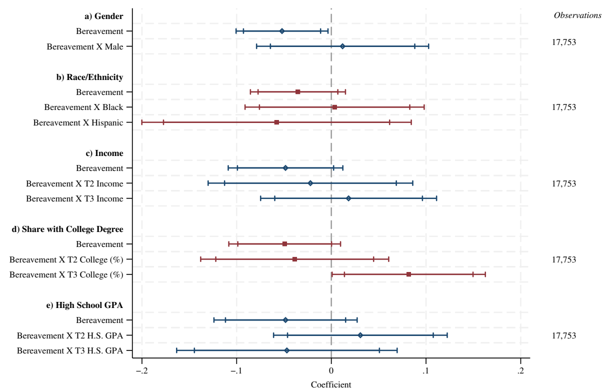
(c) Long Illness



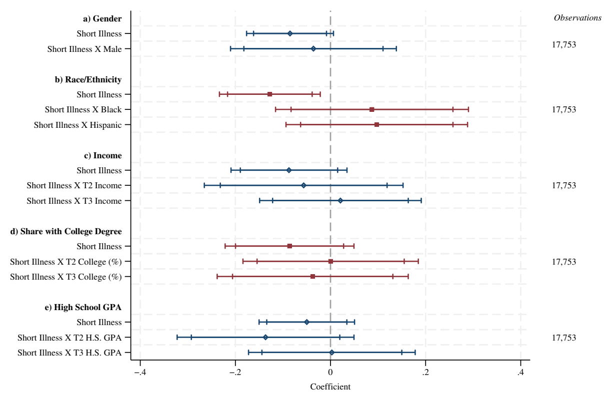
Note: The sample includes FTIC undergraduate students at a large public university from Fall 2015 to Fall 2019 for observations where they attended for less than 8 semesters. Point estimates are provided with 95% confidence intervals.

Figure A5. First-Year Students Extensive Margin Interaction Analysis, Dependent Variable: Enrolled the Next Semester

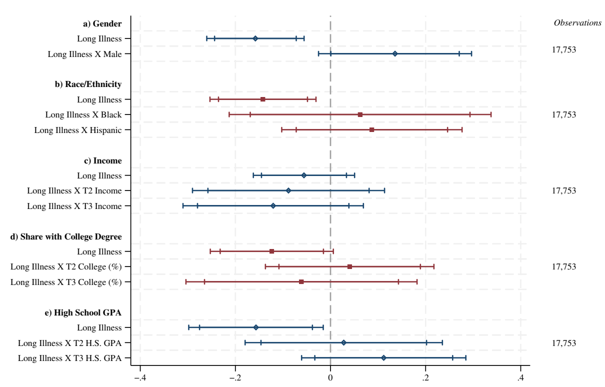
(a) Bereavement



(b) Short Illness



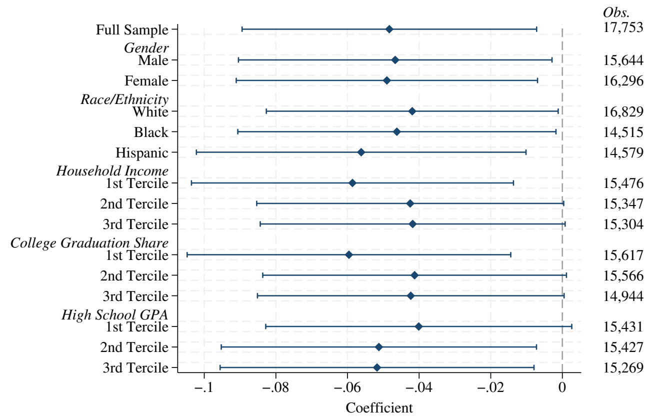
(c) Long Illness



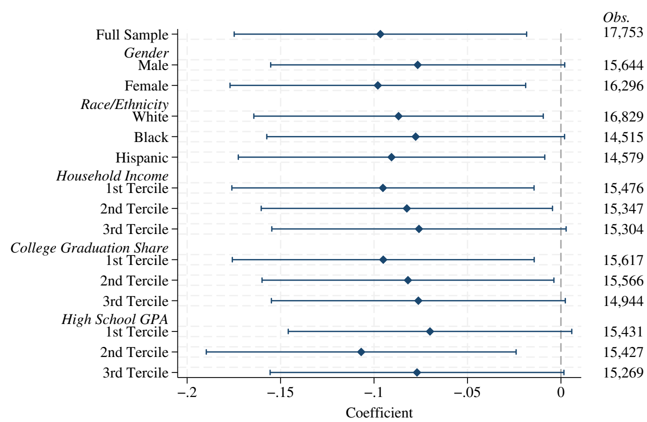
Note: The sample includes FTIC undergraduate students at a large public university from Fall 2015 to Fall 2019 for observations where they attended for less than 8 semesters. Point estimates are provided with 95% confidence intervals.

Figure A6. First-Year Students Extensive Margin Stratification Analysis, Dependent Variable: Enrolled the Next Semester

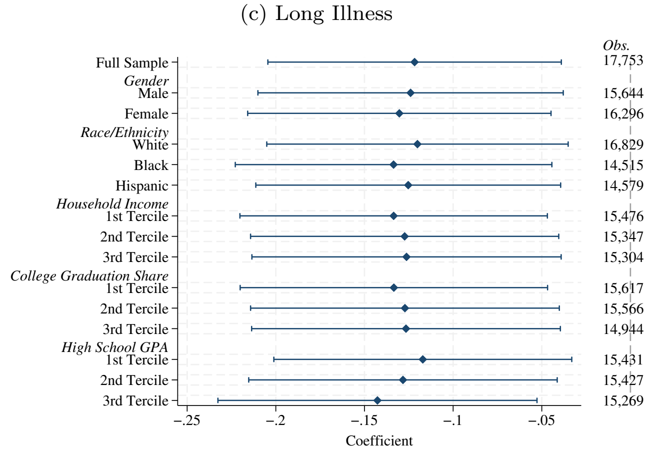
(a) Bereavement



(b) Short Illness

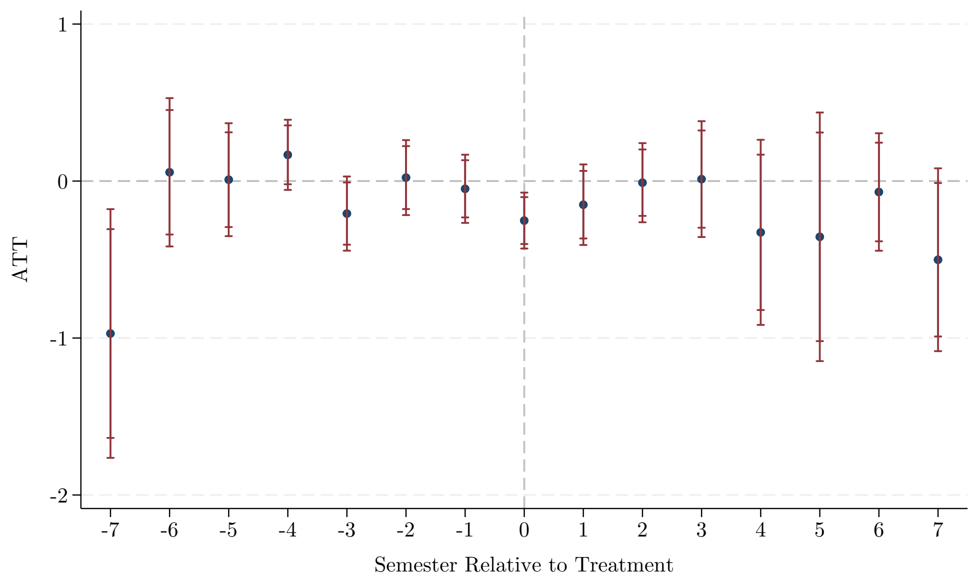


(c) Long Illness



Note: The sample includes FTIC undergraduate students at a large public university from Fall 2015 to Fall 2019 for observations where they attended for less than 8 semesters. Point estimates are provided with 95% confidence intervals.

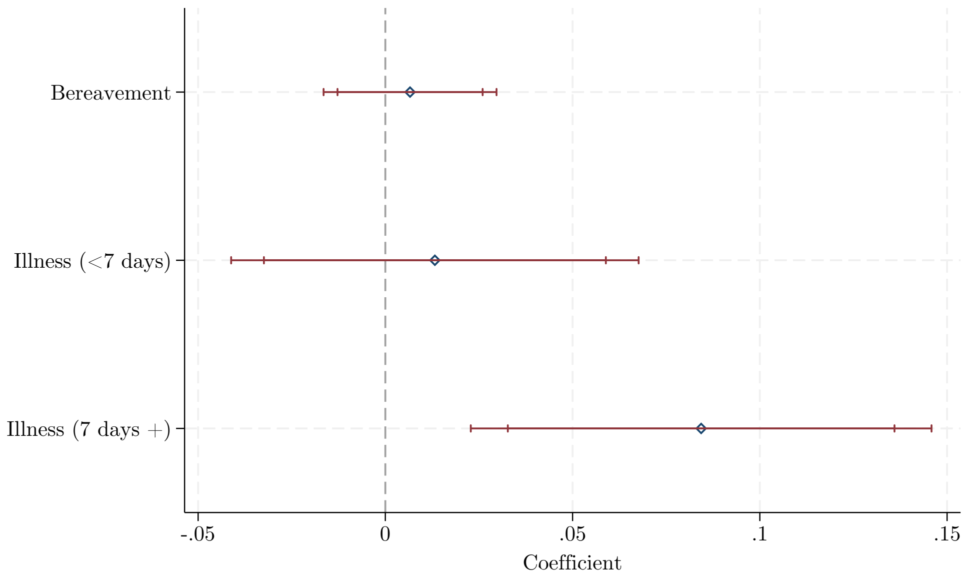
Figure A7. CSDID Estimates of the Impact of a Reported Illness of unspecified duration on Standardized Term GPA



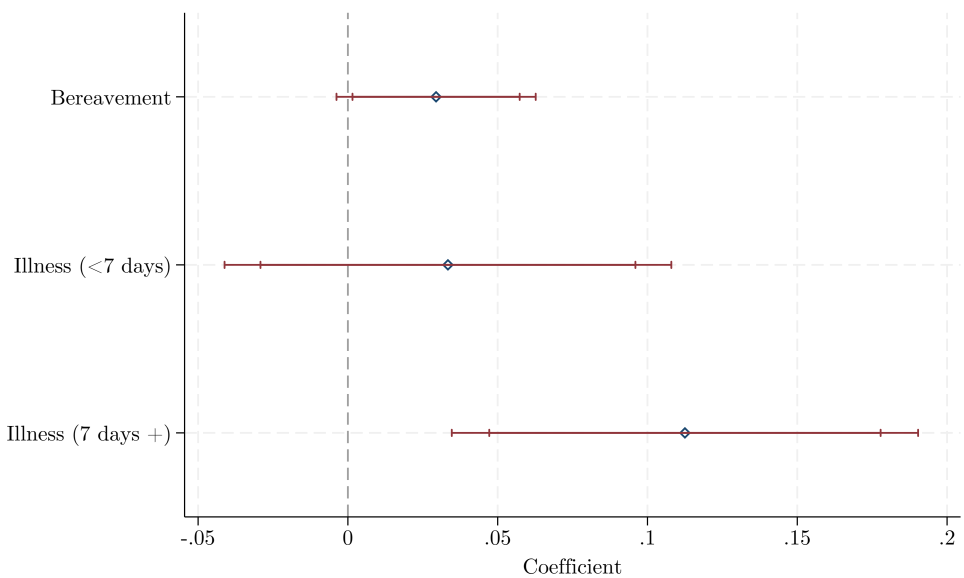
Note: The sample includes FTIC undergraduate students at a large public university from Fall 2015 to Fall 2019 excluding summer semesters who were enrolled throughout the sample period (or graduated for the Fall 2015 cohort). The sample excludes students with multiple absences of the same type. Point estimates are provided with 95% confidence intervals.

Figure A8. The Impact of Reported Absences on Withdrawing from a Course or Earning a Grade Below C (TWFE)

(a) Dependent Variable: Withdrawal from a Course

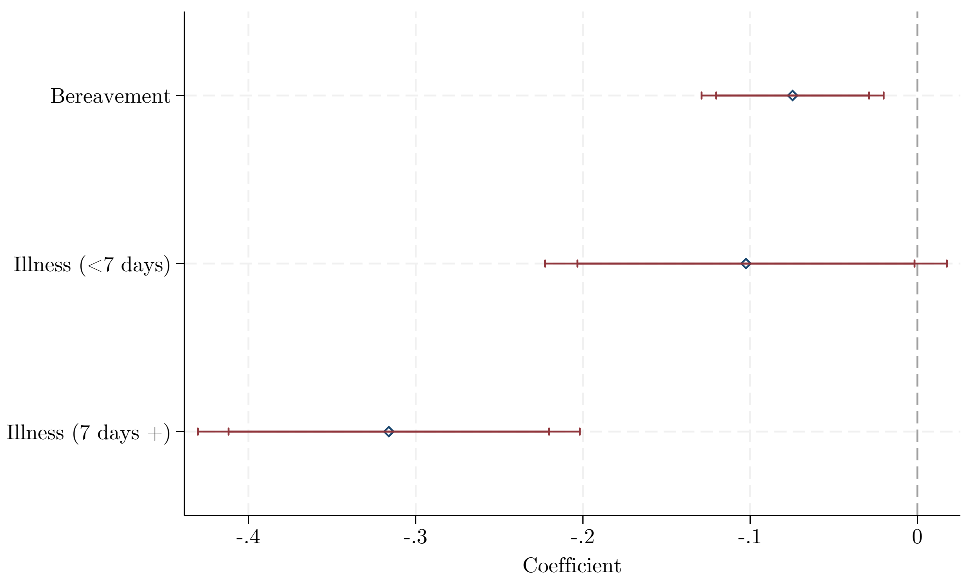


(b) Dependent Variable: Any Grade Below C



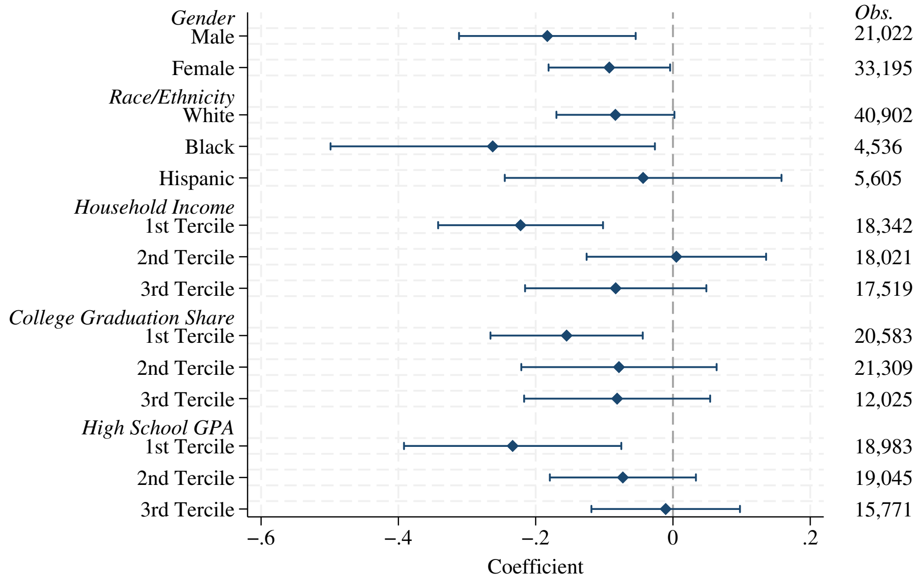
Note: The sample (N=54,744) includes FTIC undergraduate students at a large public university from Fall 2015 to Fall 2019 excluding summer semesters who were enrolled throughout the sample period (or graduated for the Fall 2015 cohort). The sample excludes students with multiple absences of the same type. Point estimates are provided with 90 and 95 percent confidence intervals.

Figure A9. The Impact of Reported Absences on Same-Term Standardized GPA (TWFE)



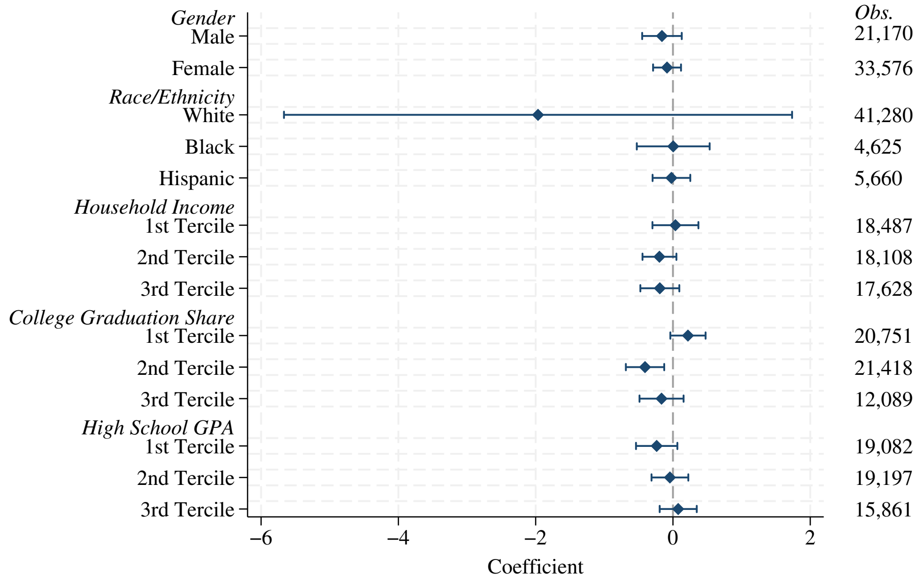
Note: The sample (N=54,481) includes FTIC undergraduate students at a large public university from Fall 2015 to Fall 2019 excluding summer semesters who were enrolled throughout the sample period (or graduated for the Fall 2015 cohort). The sample excludes students with multiple absences of the same type. Point estimates are provided with 90 and 95 percent confidence intervals.

Figure A10. Stratified Analysis: The Impact of Reported Bereavement on Standardized Term GPA (CSDID)



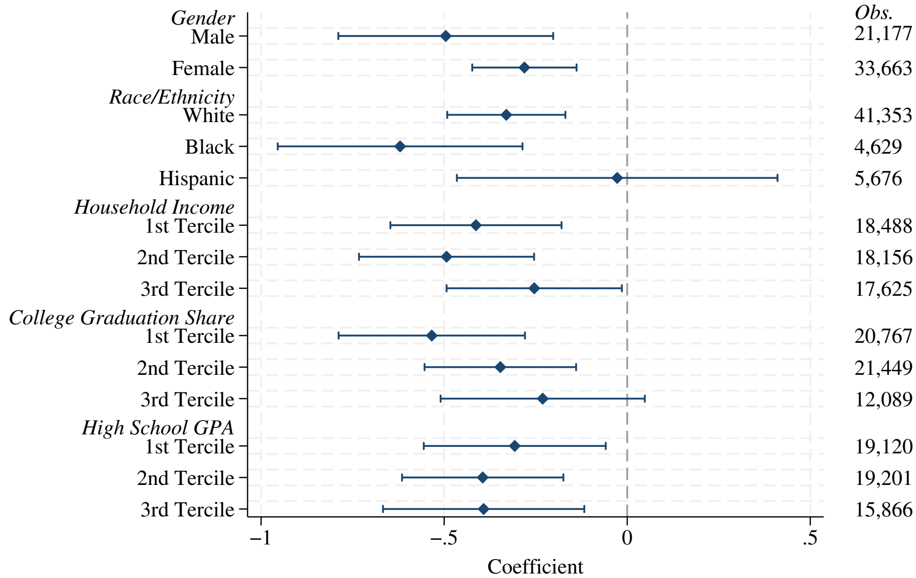
Note: The sample includes FTIC undergraduate students at a large public university from Fall 2015 to Fall 2019 excluding summer semesters who were enrolled throughout the sample period (or graduated for the Fall 2015 cohort). The sample excludes students with multiple absences of the same type. Point estimates are provided with 95% confidence intervals.

Figure A11. Stratified Analysis: The Impact of Reported Short-term Illness on Standardized Term GPA (CSDID)



Note: The sample includes FTIC undergraduate students at a large public university from Fall 2015 to Fall 2019 excluding summer semesters who were enrolled throughout the sample period (or graduated for the Fall 2015 cohort). The sample excludes students with multiple absences of the same type. Point estimates are provided with 95% confidence intervals.

Figure A12. Stratified Analysis: The Impact of Reported Long-term Illness on Standardized Term GPA (CSDID)



Note: The sample includes FTIC undergraduate students at a large public university from Fall 2015 to Fall 2019 excluding summer semesters who were enrolled throughout the sample period (or graduated for the Fall 2015 cohort). The sample excludes students with multiple absences of the same type. Point estimates are provided with 95% confidence intervals.