Bachelorette's Degree:
Financial Shocks and the Gender Performance Gap*

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Abstract

Recent research shows that labor disruptions cause female professionals to exhibit greater losses in productivity relative to their male peers. These studies attribute part of this gender-based difference to the demands of young children or other familial obligations on females. We document a reversal in this gender gap – where females on average outperform males in their resilience to financial shocks – in a setting with matched peers that is free from the confounding effects of marriage or children. Using college transcript data from the Department of Education and a triple-differences empirical design, we find that female students are less disrupted by financial shocks than male students in their human capital investment during college.

JEL classification: D14, G51, H52, H81, I22, I28, J16

Keywords: Gender gap, Performance gap, Natural disasters, Financial shocks, Human capital, Household finance

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1. Introduction

Finance and economics literature documents gender-based gaps in preferences, performance, and financial outcomes in a variety of settings. In particular, recent papers examine gender differences in the productivity shock to professional performance caused by the COVID-19 pandemic; e.g., Barber, Jiang, Morse, Puri, Tookes, and Werner (2021), Cui, Ding, and Zhu (2021), Kruger, Maturana, and Nickerson (2022), and Du (2023). Collectively, these papers indicate that (i) female professionals exhibit productivity losses relative to their male peers and (ii) part of this gender gap results from women carrying out disproportionately more childcare, domestic labor and household responsibilities (e.g., Kimmel, 1998; Bertrand, Goldin, and Katz, 2010; Bianchi, Sayer, Milkie, Robinson, 2012; Adams, Barber, and Odean, 2016; Kleven, Landais, and Søgaard; 2019; Adams and Lowry, 2022). Our contribution to this literature, reviewed in detail in the next section, is evidence of a reversal in this gender performance gap – in a setting with matched peers in college education (same classes, in the same institution, at the same time, from the same originating area) and without confounding effects of marriage or children. We document that females outperform males, on average, in their resilience to financial shocks in this setting.

Existing literature establishes natural disasters as plausibly exogenous shocks to family financial conditions affecting dependent college students who rely on their families for tuition, room and board (e.g., Cornaggia, Cornaggia, and Xia, 2024).[1] Using detailed college transcript data licensed from the Department of Education (DOE), we examine gender differences in students' productivity and human capital investment following these financial shocks – at a stage where both males and females are free from the demands of children and dependent spouses.

[1] Other papers identify financial and productivity shocks to firms based on natural disasters and resulting power outages (e.g., Barrot and Sauvagnat, 2016; Ersahin, Canayaz, et al. 2024; Giannetti, and Huang, 2024). We focus on the most disruptive disasters declared by the Federal Emergency Management Agency (FEMA), which cause damage exceeding the resources of state and local governments and require federal assistance. Damage to homes, businesses, public roads, facilities, and transportation materially affect the human capital investment and student loan outcomes of affect students; see Billings, Gallagher, and Ricketts (2023) and Cornaggia, et al. (2024) for effects of disasters on treated college students.

To illustrate our empirical design, consider a female student *A* who is enrolled in a course *X* at a university in California. During the course, there is a natural disaster in the county of Houston, Texas, where student *A*'s family lives. Student *A* is a treated student because we expect (and empirically verify) that her family's financial resources are disrupted by the disaster. Consider another female student *B* who is contemporaneously enrolled in the same course *X* as student *A* at the same university. Student *B*'s family also lives in Texas, but in Dallas County, which does not experience a disaster during course *X*. Student *B* is the control peer of *A*. We examine these two female students' performance in course *X* through the shock and trace their outcomes (including course grades and college enrollment status) surrounding the shock. This approach yields a difference-in-differences analysis for the matched treated-control female students over time. Performing the same analysis for male students yields another difference-in-differences, and contrasting these two patterns yields a difference-in-differences-in-differences.

This triple-difference setting presents several advantages. Because we benchmark treated female students against control female students as the first layer of comparison – rather than comparing female with male students – we control for general differences between male and female students in terms of physicality, academic subject matter preferences, emotional maturity, and cognitive differences (e.g. males are generally advantaged in physically demanding coursework or gravitate towards science- and engineering-related subjects more than females). These factors may introduce selection biases – e.g., females selecting STEM courses typically preferred by males could be inherently more resilient to shocks. Because we contrast students enrolled in the same courses of the same university at the same time, we control for confounding differences resulting from heterogenous class or institution characteristics (e.g., course difficulty or grading policies). Because we additionally fix students' originating location (state), we mute cross-state variation (such as education quality prior to college) among students. Taken together, this design allows us to identify gender differences in the effects of the financial shock to treated students.

With the triple-differences approach, we test whether students' academic performance, as reflected in course grades, suffers after their families experience financial shocks, and whether this difference is more pronounced among male or female students. We analyze the consequences of financial shocks in students' college continuation, and any gender differences in this human capital investment decision. We investigate whether the impact of financial shocks manifests over the longer-term, and differentially affects males' and females' academic standing throughout college and degree attainment. We explore whether these shocks influence the career paths of male and female students, particularly in finance / business and management occupations. In all these analyses, we control for a host of observable factors including students' demographic characteristics and their fields of study, their parents' background, how confident the students are (and thus how they estimate the consequence of financial shocks), and their intellectual capability prior to college (SAT scores) – which may vary by gender and simultaneously affect college outcomes.

Following financial shocks, we show that treated male students suffer drops of over two notches in their course grades relative to control male peers contemporaneously enrolled in the same course of the same university (e.g., from B+ to B-). In contrast, treated female students continue to perform similarly as their control peers on average. In the triple-differences regression with various controls, female students earn course grades that are over a half letter grade higher than treated male students after the treatment effect. This gender difference contrasts with prior evidence that females suffer greater performance losses during productivity shocks.

Such "gender gap reversal" varies with parental financial resources ex ante. Female students' greater resilience to financial shocks (compared to males) is more prominent when they come from families with low income. Among students from wealthier families, financial shocks do not cause as much disruption in performance to begin with, and females' relative resilience manifests to a lesser extent. However, the gender gap reversal presents for both white and non-white students.

We next test whether the gender gap reversal reflects a selection effect. Following financial shocks, females may be more likely than males to discontinue college enrollment, thus avoiding the adverse effects of shocks on grades (and transcripts). We find no evidence this is the case. In fact, not only do males earn relatively lower grades in the matched courses during enrollment, they are also more likely to drop out of college in the months following the shocks.

Our results on course grades and enrollment continuation highlight the consequences of financial shocks in the short term. We extend the analysis and examine the gender gap over the long run. We find that males who experience financial shocks take longer to finish their degrees and have lower GPAs when they eventually exit college. Treated females do not exhibit these negative long-term outcomes. In terms of career paths, although females in general are less likely than males to land jobs in finance or business (e.g., Adams and Kirchmaier, 2016), the financial shocks reverse this disadvantage: treated females become more likely to pursue a finance /business career than their peers without such shocks.

Together, these results indicate that the gender gap reversal is not merely transient and likely reflects gendered differences in non-cognitive characteristics in responses to adverse circumstances. Inspired by Kuhnen and Melzer (2018), we examine one such characteristic – self-efficacy – in explaining our results. Self-efficacy refers to belief that one's actions or effort can influence future outcomes. Kuhnen and Melzer (2018) show that individuals with higher self-efficacy navigate financial shocks better, leading to healthier financial standing and lower financial distress. This effect reflects individuals' perception of the benefits from effort. In the presence of financial shocks, individuals with high self-efficacy perceive their effort and sacrifices (such as studying longer hours) to be effective in turning around adversity. Therefore, they exert more effort to persevere and thrive. Those with low self-efficacy perceive their sacrifices to be inadequate to improve their circumstances, and this limited marginal benefit prevents them from spending effort.

We test whether self-efficacy explains the gender gap reversal in course performance and enrollment decisions by leveraging prior evidence that the academic self-efficacy of males and females varies across subject matter. Females exhibit higher self-efficacy in language arts or writing but are found to lack self-efficacy relative to males in mathematics, engineering, and computer science (STEM fields); e.g. Huang (2013) and Burger et al. (2010). If the observed female outperformance is attributable to self-efficacy, then it should concentrate in non-STEM fields and disappear among STEM courses. This is indeed what we find.

Overall, these results suggest that in a setting without children or family burdens females (i) achieve better outcomes compared to males facing similar adversity in non-STEM fields and (ii) achieve similar outcomes as males in STEM fields. Removing domestic obligations nullifies males' performance advantages in STEM fields and results in significantly stronger performance among females in non-STEM fields. These results complement those from Simintzi, Xu, and Xu (2024) who find that government subsidized childcare improves females' career progression. Earlier access to childcare not only increases new mothers' employment – an extensive margin effect consistent with prior literature – but on the intensive margin, it increases mothers' earnings and encourages them to pursue more demanding careers.[2] We add to the literature by documenting a reversal in the performance gender gap in an environment without children: facing an adverse financial shock during college, women perform as well as men or better.

We also consider alternative explanations for the gender gap reversal. We start by testing whether males and females compensate for the financial shocks differently – in particular, whether they have different tendency in taking up part-time employment following the shocks. We find that

[2] The extensive margin effect of access to childcare is documented in Baker, Gruber, and Milligan (2008), Goux and Maurin (2010), and Bauernschuster and Schlotter (2015).

males mitigate financial shocks by taking more part-time jobs and working more hours during college than females. However, this difference in behavior is not large enough to explain our primary results. The baseline gender gap in course performance remains robust after controlling for time-varying take-up of part-time jobs and hours worked. Additionally, males and females do not exhibit different behavior in student debt borrowing in response to the shocks; the baseline result is thus unlikely driven differential effects of related student loan indebtedness.

Our data include students' responses to survey questions about their mental status, allowing us to track changes in students' mental health around financial shocks. With this information, we test whether differences in mental resilience play a role in the observed gender gap reversal. We find that treated male and female students show equal deterioration in mental health following financial shocks. Both groups exhibit a reduction in mental health of more than ten percent of the entire range of potential responses. This result verifies that financial shocks induce mental stress (Engelberg and Parsons, 2016). However, the similarity of the effect across male and female students indicates that our main findings are not driven by gender differences in mental responses to financial shocks.

Finally, we consider the possibility that our results are spurious. If, by chance, males' families are exposed to stronger natural disasters, then our results would reflect disaster severity rather than a gender gap. We find no evidence of this explanation. Male and female students' families experience similar decreases in financial resources following natural disasters on average. Overall, we conclude that shocks to financial resources adversely affect the productivity of males more than females, on average, in the absence of marriage and children.

2. Contribution to prior literature

Prior finance and economics literature establishes gender differences in financial investment strategy (Sunden and Surette, 1998), financial risk aversion, and career choices (Sapienza, Zingales, and Maestripieri, 2009), and overconfidence and competition (e.g., Barber and Odean, 2001; Gneezy, Niederle, and Rustichini, 2003; Niederle and Vesterlund, 2007; Reuben, Sapienza, and Zingales, 2024). Much of the gender-focused literature characterizes gender differences as a gender gap whereby women face economically worse options and financially worse outcomes particularly in terms of compensation for work (e.g., Goldin, 2014; Tate and Yang, 2015; Blau and Kahn 2017; Guvenen, Kaplan, and Song, 2021; Bennedsen, Simintzi, Tsoutsoura, and Wolfenzon, 2022; Biasi and Sarsons, 2022), career advancement opportunities in finance and management positions (e.g., Benson, Li and Shue, 2024; Duchin, Simutin, and Sosyura, 2021; Sherman and Tookes, 2022; Huang, Mayer, and Miller, 2023; Ceccarelli, Herpfer, and Ongena, 2024), and other labor outcomes (Egan, Matvos, and Seru, 2022).[3] Lagaras, Marchica, Simintzi, and Tsoutsoura (2022) find that the gender pay gap is more prominent in the finance sector than others, but the second difference is shrinking over time: The difference in gender pay gap between finance and non-finance sectors was 40% in 1997 and is 23% in 2019.

One U.S. arena in which the gender achievement gap closed early is degree attainment. Prior to the passage of Title IX in 1972, women earned 43.1% of Bachelor's degrees, 38.8% of Master's degrees, and 9.6% of Doctor's degrees in the 1969-1970 academic year.[4] By 1982, women closed the gap in Bachelor's degrees (50.3%) and Master's degrees (50%) and parity in Doctor's degrees was achieved by 2006. Since then, this education gap favoring women widened nearly every year. By 2022, women earned 58.5% of Bachelor's degrees, 62.6% of Master's degrees, and 57% of Doctor's degrees. This trend is also found in US high schools; e.g., Fortin, Oreopoulus, and Phipps (2013), Reeves, Bucker, and Smith (2021).

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[3] Pharmacists are a noteworthy exception among college graduates; technological advancement increases substitutability among pharmacists and reduces the penalty to part-time work in this industry, thus narrowing the gender earnings gap; Goldin and Katz (2016). The broader gender promotion gap is studied in Bertrand and Schoar (2003), Matsa and Miller (2011), Cullen and Perez-Truglia (2019), Azmat et al (2024), Giorcelli (2024), and Haegele (2024).

[4] The Digest of Education Statistics from NCES (Table 318.10) documents degrees conferred by postsecondary institutions, by level of degree and sex of student for selected year from 1869 – 2022. Updated data are available here: https://nces.ed.gov/programs/digest/d23/tables/dt23_318.10.asp

Analogous to gender differences in human capital investment are gender differences in housing investment, where women likewise earn lower financial returns; Goldsmith-Pinkham and Shue (2023). These authors conclude that the gender gap reflects differences in execution prices more than gender-based differences in upgrades, maintenance, or property types. However, the gender gap in housing investment performance varies with market cycles. As housing supply tightens – increasing the value of housing investment – the gap shrinks to zero.

Closely related to our study are the recent papers documenting a gender gap in the impact of COVID-19 on worker productivity. Du (2023) finds that female analysts with children are less likely to issue timely forecasts after school closures compared to male analysts with children. Mother analysts' forecasts also become less accurate. Cui, et al. (2021) find productivity gains in academic research in the two years spanning the lockdowns across 18 disciplines covered by the Social Science Research Network (SSRN); but these gains accrue disproportionately to male researchers. The gender gap is pronounced for assistant professors and attributed, at least in part, to women's responsibilities at home. In a similar study, Kruger et al. (2022) focus on research in finance and economics and find productivity gains to men and women – with the exception of women between the age of 35 and 49 (i.e., those most likely responsible for childcare during school closures).

Barber et al. (2021) also focus on finance research productivity following COVID-19 with a survey of American Finance Association (AFA) members. They find that productivity falls more for women, faculty with young children, faculty with greater teaching responsibilities, and faculty more concerned about the financial viability of their employers. An important insight from this study is that while the presence of young children adversely affects the productivity of men as well as women, women are more negatively impacted by the shock, holding family structure constant – due in part to women allocating more time to childcare given the same family structure. In a setting absent of productivity shocks, Adams and Lowry (2022) survey AFA members and find that overall, women's job satisfaction is significantly worse than men's in finance academic occupations, potentially due in part to childcare responsibilities.

Given potentially confounding effects of gender-based variation in teaching burdens, financial strength of employing institution, childcare responsibilities (controlling for number of children), as well as the interaction of childcare demands with other factors (such as bias), our laboratory offers a unique opportunity to examine any gender-based differences in a less confounded environment. In a triple-difference setting with matched educational preferences, intellectual aptitude, and workload – but free from confounding effects of marriage or children – we document less performance loss from females relative to males, on average, following an adverse financial shock.

3. Data sources

3.1. Beginning Postsecondary Students Longitudinal Study (BPS)

The National Center for Education Statistics (NCES), part of the Department of Education's Institute of Education Sciences (IES), is responsible for collecting and analyzing education data. We use the NCES Beginning Postsecondary Students Longitudinal Study (BPS), which surveys a representative sample of students who are starting their postsecondary education for the first time at eligible U.S. institutions.[5] This database provides information on a range of topics, including student demographics (such as gender, race, and age), educational and work experiences, academic transcripts, and family financial information. Eligible institutions for the BPS are those that meet all the criteria for distributing federal aid under Title IV of the Higher Education Act. For our analysis, we use data from the most recent cohort of students who entered college in the 2011-2012 academic year, referred to as BPS12, which contains information on the

[5] To be eligible for the BPS, students must be enrolled in an academic program, at least one for-credit course that counts toward an academic degree, or an occupational or vocational program that requires a minimum of three months or 300 clock hours of instruction to obtain a degree, certificate, or other formal award. Students who are also enrolled in high school or high school completion programs are not eligible.

geographical locations of student families. In the following subsections, we describe the detailed datasets of BPS.

Our license to use these data requires that we round all sample sizes to the nearest 10. The BPS provides survey weights to ensure that the sample accurately represents the population of first-time students. These weights account for sampling procedures, nonresponse adjustments, and poststratification adjustments. Our analyses use these weighted data, and estimates are based on these weights for panel analysis.

3.1.1. Student transcripts

BPS12 includes transcript information, including students' coursework, grades, credits, and course characteristics such as the classification of a course field. For each student experiencing a family shock, we identify control students of the same gender who are enrolled in the same courses at the same university during the same semester but do not experience any concurrent family shocks. This approach has two advantages. First, it minimizes potential differences between male and female students in terms of physicality (e.g., males are generally advantaged in physically demanding coursework), academic preferences (e.g. males are more likely gravitate towards STEM), emotional maturity / perseverance (e.g., females earn higher GPAs and are more likely to graduate; Conger and Long, 2008; Reves and Smith, 2021) – which may introduce selection biases: for instance, female selecting certain courses may be extraordinarily more reliant to shocks than males. Second, the requirement of contemporaneous enrollment in the same course of a university minimizes confounding differences related to varying class or institutional characteristics, such as course difficulty or grading policies.

3.1.2. Family financial information from Free Application for Federal Student Aid (FAFSA)

We focus our empirical analyses on dependent students who rely on their parents' income to finance their college expenses. The Department of Education determines dependency status each year using the FAFSA.[6] This filter ensures that all students in our sample are unmarried and have no children or dependents. The annual FAFSA also collects key parental financial information from tax filings in order to calculate the Expected Family Contribution (EFC); it includes parental gross income (earnings), savings, and tax paid (proxying for total income). We use these data to validate that disruptive disasters significantly deteriorate families' financial conditions, generating a meaningful shock to college students. We also test whether the differential effects of financial shocks on male and female students vary with their family wealth, which allows us to derive heterogeneity in the gender gap.

3.1.3. Students' family locations

The BPS12 provides students' permanent addresses at the beginning of their college enrollment. These addresses serve as proxies for dependent students' parent residence locations. Using these data, we can differentiate between shocks experienced by student families at their parents' residences versus those experienced directly on campus (or in neighborhoods adjacent to campus) by students while they are enrolled in school.

3.1.4. Enrollment and other characteristics

In addition to examining students' course grades following financial shocks, we also analyze their continuation of college enrollment. The BPS12 contains information on whether a student is enrolled in college as of each month. This information allows us to track students' persistence in human capital investment when facing financial shocks.

Lastly, the BPS interviews students at three points in time to collect college experience data: at the end of their first year of enrollment, and then three and six years thereafter. Collected information includes academic standing, degree attainment, and post-college occupations. We use this information to study the long-term differential effects of family shocks on male and female

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[6] Details on how the DOE determines dependency status are available here: https://studentaid.gov/apply-for-aid/fafsa/filling-out/dependency

students.

3.1.5. National Student Loan Data System (NSLDS)

The BPS12 data are supplemented with Federal Student Aid (FSA) administrative records from the National Student Loan Data System (NSLDS). This dataset includes histories of federal loan receipts and repayments from the distribution of each loan up to December 2017. In part of our analyses, we investigate whether male and female students borrow student debt differently in response to family financial shocks, and whether the gender gap is attributable to borrowing behavior.

3.2. Federal Emergency Management Agency (FEMA)

The FEMA Disaster Declarations Summaries dataset provides information on disaster types, start and end dates, and the affected states and counties. The start and end dates help estimate the duration of each disaster, while the scale of assistance reflects the severity of both public and personal damage associated with the event.

Details about *Public Assistance* (PA) projects are from the FEMA *Public Assistance Funded Projects Details* dataset. PA projects include repairing, replacing, or restoring disaster-damaged public facilities, removing debris from public areas, and conducting emergency protective measures like search, rescue, and evacuation. Sanstad, et al. (2020) show that the impact of public damage on households largely comes through industrial employers. When firms close facilities and are unable to operate machinery or manufacture products, households may suffer wage losses. Tuzel and Zhang (2017) further find that shocks to local firms may be aggregated by immobile local factors (including wages and rents). We calculate the total cost of public damage as the sum of federal grants for all PA projects related to a specific disaster.

For personal damage, we use data from the FEMA *Individuals and Households Program - Valid Registrations* dataset, which provides applicant-level information under the *Individuals and*

Households Program (IHP). This dataset includes FEMA-assessed damage values for real property, including floors, walls, electrical systems, plumbing, HVAC systems, appliances, and furniture. The total cost of personal damage is the sum of damages to real and personal property for all registered applicants affected by a disaster. Damage to personal property poses direct financial challenges to households. Taken together, Cornaggia, et al. (2024) show that major disasters lower household income, raise unexpected expenses (thus reducing savings), and diminish families' ability to fund education. Approximately 92% of federally declared disasters provide PA, while about 27% offer IHP.

These datasets enable us to identify the most disruptive disasters. We define a student as exposed to a shock if they come from a county that experienced a significant disaster. This approach is consistent with prior research on financial shocks to firms based on natural disasters affecting their headquarters' locations (e.g., Barrot and Sauvagnat, 2016; Ersahin, Giannetti, and Huang, 2024). However, a limitation is that our data do not specify the extent of impact on each family or on a per capita basis. Therefore, the estimated effects are intent-to-treat effects, providing a lower bound on the actual treatment effect.

4. Sample and descriptive statics

Our sample period spans academic years 2012 through 2018. The Department of Education defines an academic year as running from July to June (e.g., July 2017 to June 2018). The BPS12 cohort first enrolls in college in 2012 and most students graduate (or leave school for other reasons) by the conclusion of the academic year 2018. Online Appendix Figure A1 presents the total number (Panel A) and average duration (Panel B) of federally declared natural disasters experienced by each county over the sample period. The range of occurrence is zero to nine. The geographic dispersion of disasters across counties within states is important because our identification strategy compares students originating from the same state.

We focus on *disruptive* disasters by selecting those with above-median total damage (the sum of public and personal) and above-median duration among all federally declared disasters in the sample period. Total damage reflects the severity of the disaster. Recent research on salience and economic behavior motivates the duration filter. Bordalo, Gennaioli, and Shleifer (2022) define a salient stimulus as one that captures a decision maker's attention, potentially diverting it from their original goals. We posit that natural disasters serve as salient stimuli, distracting students from their coursework and impacting their performance. Mrkva and Boven (2020) demonstrate that repeated exposure to a stimulus increases its salience and affects decision-making more significantly. In the case of natural disasters, long-duration disasters provide prolonged exposure to such distractions, likely having a greater impact than shorter disasters. In our sample, disasters with above-median duration last about 28 days on average, compared to only 2 days for below-median duration disasters. This difference is relevant given that an academic semester lasts about 15 weeks.

We define treated students as those who are classified as dependent by the DOE and come from a county affected by a disruptive disaster during a semester in our sample period.[7] Each treated student is matched with control students of the same gender, who are also dependent, also enrolled in the same courses at the same institution, but whose families do not experience any FEMA-designated disasters during that semester. We exclude treated students for whom there are no control students who meet these criteria, and those at institutions directly affected by disasters to avoid confounding effects (e.g., affected schools reducing resources to support student academic achievement). After applying these criteria, our sample consists of about 1,860 treated students.

Table 1 Panel A provides summary statistics for the disasters in the sample. (There are about 60 disasters in the sample. We omit this figure from the table per IES requirements.) Severe

[7] Overall, about 6,600 out of 25,910 students in the BPS12 database have families affected by disruptive disasters between 2012 and 2018.

storms are the most common disaster. Although hurricanes are the third-most common disaster, they are the costliest, both in aggregate and on a per-event basis, with an average (median) total cost of about $1.5 billion ($141 million). The sample also includes less common disasters such as fires, earthquakes, snowstorms, mudslides, and landslides.

[Insert Table 1 here.]

Table 1 Panel B provides summary statistics at the disaster-county level. The first three columns summarize damages in millions of U.S. dollars (in total, as well as disaggregated by public and personal damages), the number of IHP applicants from affected counties, and disaster durations measured in days. For context, the next three columns replicate these statistics for Hurricane Harvey, the second-most costly storm in U.S. history. The average county-level damages in our sample ($174 million) exceed those of Hurricane Harvey ($111 million), largely due to Hurricane Sandy, the costliest storm in US. history. At the median, total damages in our sample ($9 million) are less than half of those from Harvey ($22 million). Median personal damage costs ($1.4 million) and the number of IHP applicants (911 households) indicate that our sample disasters are approximately half the size of Harvey ($2.5 million and 1,962 households).

The bottom rows of Panel B show that conditional on experiencing a disruptive disaster, the number of disasters experienced by an average student is 1.2 disasters during the sample period. The unconditional average is 0.48, indicating that most students do not face disasters during this time. These "clean controls" are less likely to be affected by heterogeneous treatment effects (e.g., Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; Goodman-Bacon, 2021). We include all control students in our main analyses to increase sample size and testing power. For robustness, we replicate results with clean controls (about 71% of all control students) and estimate the Sun and Abraham (2021) estimator in Online Appendix, Figure A4.

Table 2 provides summary statistics on characteristics for the students and families in our sample for each gender. Treated students are those from counties hit by disasters, and control students are those taking the same course in the same university at the same time but are from counties not hit by disasters.

[Insert Table 2 here.]

For both genders, treated and control students have similar characteristics, supporting the assumption that family shocks due to natural disasters are plausibly exogenous. Among the sample of female students, both treated and control groups are predominantly white (67.7% vs. 62.9%), with no significant economic or statistical differences. Treated female students are older by 0.089 years, or about 32 days, a difference that is marginally statistically significant at the 10% level. This difference, however, is economically trivial. For treated versus control male students, there are no significant differences in the percentage of white students or in their ages. Students in all groups (treated females, control females, treated males, control males) have SAT scores around 1,100. Parents of students in all groups have similar rates of college degree completion (ranging from 34.7% for control females to 39.5% for treated males), taxes paid, earnings, savings, and number of children in college. These similarities suggest that family shocks from natural disasters do not disproportionately affect disadvantaged students. We also observe no differences in treated versus control students' confidence that they can succeed as a student, or in the likelihood that treated versus control students are non-traditional students.

5. Analysis

The thought experiment underlying our empirical design is as follows. Consider two female students *A* and *B*, enrolled in the same course of the same university in California at the same time. Both students originate from Texas. Student *A*'s family lives in the county of Houston; student *B*'s family lives in Dallas. During the course, there is a major disaster in Houston but not in Dallas. Student *A* is identified as the treated student as we show that her families' financial resources are significantly disrupted by the disaster, compared to the control peer *B*. We then examine these two female students' performance in the common course during the shock and trace their other academic outcomes surrounding the shock.

This approach yields a difference-in-difference analysis across the matched treated-control female students over time. Performing the same analysis for male (similarly matched) yields another difference-in-difference pattern, and contrasting these two patterns yields a difference-in-differences-in-differences setting.

5.1. Natural disasters as financial shocks

As a first step, we verify that natural disasters create financial shocks for the parents of treated students (without differentiating student genders).[8] For each treated student *A* and control students *B* (enrolled in the same course of a university at the time of the shocks), we examine their family financial conditions around the shock, including parents' income taxes paid (as a proxy for total income), earnings, and savings.[9]

We estimate an OLS regression model as follows:

$$Family\ financials_{i,t} = \alpha + \sum_{t=-2}^{2} \beta_{1t} \times Treated_i \times I_t + \beta_2 \times Treated_i$$
$$+ \sum_{t=-2}^{2} \beta_{3t} \times I_t + \beta_4 \times Student\ and\ Family\ Charateristics_i + Fixed\ effects + e_{i,t}\ . \quad (1)$$

Dependent variables are students' family financial variables in a given year. To capture family financials relative to the price of education, we scale these variables by the 2012 academic year tuition, which is calculated as the average of each school's in-state and out-of-state tuition collected by NCES. The independent variables of interest are the interactions between *Treated* and event time indicators (denoted as I_t) before and after *Year 0* – the year end when treated student experiences the family shocks. *Year -1* (or *Year 1*) includes the year before (or after) *Year 0*. *Year -2* (or *Year 2*) includes the second year before (or after) *Year 0*. We omit the pre-shock year (*Year*

[8] In Section 6.4, we examine whether natural disasters, by chance, differently hit the families of male and female students.

[9] Because the DOE assigns a zero value to all family financial variables if a student's parents earn an annual income below $31,000, a drop in these variables across this threshold exaggerates the actual deterioration in family financials. We therefore focus on the trend around the shock rather than levels.

-1) interaction as the baseline.[10]

The coefficient of each interaction (β_1) indicates whether treated and control students exhibit different family financials in a year, relative to the pre-shock year. We include *Course-semester* × *Fam. State* × *Event time* fixed effects. *Course-semester* ensures that treated and control students are enrolled in the same course in the same semester of the same university; *Fam. State* ensures that these students originate from the same home state; *Event time* forces comparison in a given event year. These fixed effects absorb the event year indicators (and their coefficients β_3). Controls include *Female*, *White*, *Age*, *Parents' college degree*, *Number in college*, *Non-traditional index*, and student field of studies.[11]

Figure 1 plots the regression coefficients of the interaction terms β_1, and Table A1 in the Online Appendix presents the regressions.

[Insert Figure 1 here.]

Panel A of Figure 1 shows that the parents of treated students experience a statistically significant decrease in taxes paid (proxying for total income) in the year of the natural disaster (*Year 0*). Panels B and C show this effect is accompanied by significant decreases in earnings and savings, respectively. Across all three measures, the effect is most prominent in the year of the disaster, consistent with Deryugina et al. (2018).

To interpret the economic magnitudes, consider Panel B as an example. The negative coefficient of -1.4 in *Year 0* suggests that relative to the controls, parental earnings of treated students decrease by about 1.4 times the college tuition during the disaster year (recall that family financial variables are scaled by the price of education). This effect becomes marginally

[10] We line up event time with information in the corresponding tax year for ease of interpretation, based on FASFA's "prior year" rule (before 2017) and "prior-prior year" rule (since 2017). In this way, the "Year 0" shown can be directly interpreted as the event year relative to the occurrence of disasters. For more details about the prior-prior year rule, see https://fsapartners.ed.gov/sites/default/files/2021-03/1718AVG.pdf.

[11] Following CCX (2024), we exclude students if their EFC is zero. These students typically rely on external financing, such as federal loans and grants, thus making financial shocks to parents less relevant.

insignificant in the following year (*Year 1*), and the point estimate reduces to -1. Panel A depicts similar magnitudes (assuming an average tax rate of 10%-20%). In Panel C, declines in parental savings of treated students amount to about 50% of the tuition in *Year 0*, and 100% in *Year 1*.

The effect of disasters loses statistical significance two years after the disaster for all three measures. However, point estimates for all three measures remain lower than their benchmark values in the year prior to natural disasters. Overall, these results in Figure 1 and Table A1 validate that natural disasters have negative and significant financial consequences for students' families.

5.2. Do financial shocks affect males and females equally?

In this section, we examine whether financial shocks due to nature disasters differentially affect female and male students, as captured by their course grades. An ideal test design – akin to that in Section 5.1 – would be for each treated student *A* and matched control students *B* of the same gender (in the same course), we trace how the grades of this pair's common courses change around the family shock. This design, however, significantly reduces our sample (by over 60%) because in practice, students *A* and *B* do not always enroll in the same courses at the same time throughout college – due to individuals' different agendas and progress. Therefore, we employ a modified design that relaxes the selection of control students.

Specifically, for each female treated student *A* who experiences a family shock when enrolled in course *X*, we look for courses *Y* taken by student *A* before and after the shock, and compare the performance of *A* with the performance of other female students contemporaneously enrolled in *Y*. Here the control students do not need to be student *B* (who are simultaneously enrolled in course *X* during the shock), and can be any female students that do not experience family shocks at the time of common courses *Y*. This modified design allows us to preserve a sizable sample for further heterogeneity tests (Section 4.3). In Online Appendix Table A2, we repeat our analyses using the aforementioned ideal test design; despite a small sample, we confirm our findings.

We estimate the following equation, separately for female and male students:

$$Course\ grades_{i,t} = \alpha + \sum_{t=-2}^{2} \beta_{1t} \times Treated_i \times I_t + \beta_2 \times Treated_i + \sum_{t=-2}^{2} \beta_{3t} \times I_t + \beta_4 \times Student\ and\ Family\ Charateristics_i + Fixed\ effects + e_{i,t}\,. \quad (2)$$

The dependent variables are course grades translated and normalized by DOE to a four-point GPA scale for comparable basis. For example, a grade is normalized to 4.0 if it is "A+", "A", or between 93 and 100, and to 3.7 if it is "A-" or between 90 and 93, and so forth. The independent variables of interest are the interactions between *Treated* and event time indicators. If a course occurs in a semester within one year before (or after) the semester when the treated student experiences a family shock (time 0), then it is included in the sample of *Year -1* (or *Year 1*). If a course occurs in a semester between one and two years before (or after) time 0, then it is included in the sample of *Year -2* (or *Year 2*). The coefficients β_1 capture how treated and control students perform in common courses, relative to the pre-shock period. Similar to Equation (1), we include *Course-semester* × *Fam. State* × *Event time FE.*[12]

Figure 2 plots the coefficients of β_1, separately for female and male students. The dashed line presents a difference-in-difference estimation among female students, and the solid line presents a difference-in-difference estimation among male students.

[Insert Figure 2 here.]

The dashed line shows that treated and control female students have no significant differences in grades prior to treatment students experiencing financial shocks – again confirming that the family shocks from natural disasters are likely random. Importantly, differences in their grades remain negligible after natural disasters, with some evidence that treated female students earn slightly higher grades in the year after disasters relative to control female students. For male students, a different pattern emerges. Treated and control male students have similar grades in the

[12] Controls include variables in column (3) of Table 3 below. Standard errors are clustered at the student origin county and student level.

years prior to financial shocks. However, treated male experience significantly worse academic performance in the year of a natural disaster relative to control male students. The effect is large (approximately 0.7 grade points on a 4.0 scale), statistically significant, and it persists through the following two years.

We replicate Figure 2 using the Sun and Abraham (2021) estimator to account for the potential heterogenous treatment effect. Control students under this approach consist of those whose families never experience natural disasters over the sample period (i.e., the "clean" controls). See Figure A4 in the Online Appendix. There we observe that the patterns for female students are nearly unchanged. However, for male students, the negative effect of financial shocks is somewhat stronger. Two years after natural disasters, treated male students experience academic performance that is worse by a full letter grade relative to control male students.

These patterns indicate that male students react differently to financial shocks than female students. Whereas treated female students continue to perform similarly in their coursework following financial shocks relative to control female students (the dashed line), treated male students' performance suffers significantly relative to control males (the solid line). The contrast of these two patterns yields a triple-differences (DDD) analysis, and we formalize this analysis in Table 3. Specifically, we estimate the following OLS regression:

$$Course\ grades_{i,t} = \alpha + \beta_1 \times Treated_i \times Post_t \times Female_i + \\ Interaction\ terms\ and\ standalone\ indicators_{i,t} + \beta_4 \times Student\ and\ Family\ Charateristics_i + \\ Fixed\ effects + e_{i,t}\ . \qquad (3)$$

where *i* indexes student and *t* indexes time. Unlike Equation (2) and Figure 2 that report separate estimates for each year in event time, here we construct an indicator variable *Post* that equals one in the year of the natural disaster and the two years following, and zero in the two years prior to the disaster. (This approach avoids a cumbersome regression output with seven triple-interaction terms, one for each event year.) The specification is a multivariate DDD analysis. As before, we cluster standard errors at the student-origin county and student level. If, following financial shocks, treated female students earn similar grades (relative to the control female), whereas treated male students perform worse as suggested by Figure 2, then β_1 should be positive and significant. Table 3 reports the results.

[Insert Table 3 here.]

Column (1) in Table 3 shows that, after males and females experience financial shocks, females respond by earning course grades that are 0.397 points higher than males (on a 4.0 scale), benchmarked against their respective control peers. This estimate is statistically significant at 5%. Column (2) replicates this analysis after controlling for student characteristics beyond gender, including age, whether the student is non-traditional, confident in their abilities as a student, SAT score, field of study fixed effects, as well as students' family characteristics, including whether their parents have college degrees and how many children they have in college. The differential effect of financial shocks on grades grows to 0.430 points. Column (3) again replicates the analysis after controlling for economic and demographic characteristics of the location where students' families reside, including the median family income, percentage of unemployed population, and percentage of white population in the area. The effect grows further, to 0.465 points. This magnitude translates to a 1.5-notches difference (a one-notch difference is between e.g., B and B-), or over a half letter grade difference.

Columns (4) and (5) repeat the analyses in columns (1) to (3) using the subsample of white versus non-white, respectively. This split significantly reduces the non-white subsample because of our restrictive identification strategy: for a non-white treated student *A* enrolled in course *X*, if we cannot identify any control students who are also non-white, simultaneously enrolled in *X*, and originate from the same state as *A*, then the entire course *X* (and its students) will be excluded from the regressions.

We find robust results across races: after experiencing financial shocks, both white and non-white females earn higher course grades than males who also experience financial shocks. The magnitude of the effect is larger in the non-white subsample, although the coefficient is marginally statistically significant at the 10% level due to the limited sample.

5.3. The role of family finances

The results so far indicate that females respond to financial shocks with greater resilience than males – a gender gap in the opposite direction of recent studies documenting females suffer greater productivity losses, on average, during shocks. We next examine whether this gender gap reversal varies with family financial resources. We perform this test in Table 4 by splitting the sample into above- and below-median subsamples based on family financial resources (i.e., parental income or earnings) prior to the shock (i.e., in *Year -1*).[13] To conserve space, we only present the results based on earnings. Conclusions are similar using parental income.

[Insert Table 4 here.]

Columns (1) and (2) include the subsample of students whose parental earnings are below the sample media, and columns (3) and (4) include those with high-earning parents. Columns (2) and (4) include additional controls for the demographics and characteristics of students' originating locations. We find that the gender-based performance gap is only present in the low-earnings group, as indicated by the positive and significant coefficients of *Treated* × *Post* × *Female* in columns (1) and (2). More specifically, in column (2), treated male students from lower earning families underperform their male peers by 0.883 grade points (out of 4 points), as shown by the coefficients of *Treated* × *Post*. Female students, however, eliminate this performance drop, and their course grades show no significant difference compared to the control (i.e., the summation of

[13] We do not use parental savings to split the sample because of missing values for this variable. See Table A1 in Online Appendix.

Treated × *Post* and *Treated* × *Post* × *Female*: -0.883 + 1.251). Put differently, relative to their respective peers, treated female students outperform treated male students by 1.251 grade points.

In contrast, in column (4), male students' grades do not change significantly (*Treated* × *Post* = 0.040) and females' greater resilience disappears (*Treated* × *Post* × *Female* = -0.002). As such, we conclude that family financial resources mitigate the gender gap in performance following financial shocks.

5.4. Is there a gender performance gap on the extensive margin?

The results show a gender gap in course performance among students who remain enrolled in college following financial shocks. This finding could reflect a selection effect, whereby females discontinue college enrollment at higher rates than males following financial shocks. If that is the case, then the greater resilience of females in response to shocks would reflect their "dodging" poor performance. To investigate this possibility, we examine the extensive margin: Are treated female students more likely to drop out of college than treated male students? We find the opposite.

For each treated student *A* and control students *B* (in the same course of a university at the time of the shocks), we trace their college enrollment surrounding the shock. We estimate a similar regression as in Equation (1) and Equation (2) in a monthly panel data, in which the dependent variable is an indicator for whether a student remains enrolled in college as of each month end. *Month 0* denotes the month when the shock occurs. The coefficients of the interactions between *Treated* and event time indicators test whether treated and control students exhibit different enrollment status in a month, relative to the pre-shock month (i.e., *Month -1*). Panel A of Figure 3 plots these coefficients estimated among female students.

Relative to the pre-shock month, we observe no significant changes in females' enrollment status following the shocks: Treated female students are equally likely to remain enrolled after the shocks than control female students. Panel B of Figure 3 shows a different pattern for males. Treated male students are less likely than control male to remain enrolled following the shocks.

The effect attains statistical significance two months after the disaster and reaches its largest (negative) magnitude seven months after the disaster. The effect dissipates and treated male students regain their enrollment as control male students beginning eight months after the shocks – approximately one academic year after the shocks. This figure suggests that female students exhibit greater perseverance than male students upon encountering financial shocks.

[Insert Figure 3 here.]

As in Figure 2, the contrast between Panels A and B yields a DDD analysis, which we formalize in Table 5. Given the evidence in Table 4, that the gender gap in course performance following financial shocks varies with family financial resources, we split the sample based on parental earnings prior to the shocks.[14] The specification and control variables follow Equation (3). Post equals one for observations from *Month 0* to *Month 9*, and zero for observations from *Month -3* to *Month -1*.

[Insert Table 5 here.]

Columns (1) and (2) feature students with parental earnings below the sample median and columns (3) and (4) feature those with high parental earnings. Column (2) shows that male students with low-earning parents are 12.1% more likely to discontinue enrollment following the shock, relative to their male peers (i.e., the coefficient of *Treated* × *Post*: -0.121). Treated female students with low-income parents, however, are equally likely to remain in enrolled as the control (the summation of the coefficients of *Treated* × *Post* and *Treated* × *Post* × *Female*: -0.121+0.160). In other words, treated male students are 16% more likely to drop out of college in the months following natural disasters than female students. In contrast, column (4) shows no statistical or economic difference when male and female students have high-earning parents, as captured by the insignificant coefficients of *Treated* × *Post* × *Female*.

[14] Results are again similar using taxes paid, proxying for total parental income.

5.5. Do financial shocks lead to gender gaps and different career paths over the longer term?

The DDD analyses above indicate that benchmarked against peers of the same gender, financial shocks cause males to underperform in their college courses relative to females and more likely to discontinue college enrollment. This section tests whether gender performance gaps extend to longer-term outcomes. In particular, we test whether treated female students are more likely than treated male students to earn higher overall GPAs during college, earn college degrees in a timely manner, and land jobs in management or finance / business. Different from the previous DDD analyses, these outcomes variables are snapshots at the conclusion of college. We therefore estimate the following modified model:

$$Long - term\ Outcome_i = \alpha + \beta_1\ \times Treated_i \times Female_i + Standalone\ indicators$$
$$+\beta_2 \times Student\ and\ Family\ Charateristics_i +\ Fixed\ Effects + \varepsilon. \qquad (4)$$

This approach is a multivariate difference-in-differences (DD) analysis, and the key coefficient is β_1. This coefficient captures whether treated female students experience different outcomes after the conclusion of college than control female students (enrolled in the same course at the same time during the shock) – and contrasts this difference with that between treated and control male students. Because there is no event time variation in this analysis, we only include *Course-semester* × *Fam. state* fixed effects, which force comparison between treated and control students enrolled in the same course at the same time and originating from the same home state. We cluster standard errors as in the previous tests. Table 6 presents the results.

[Insert Table 6 here.]

Column (1) of Table 6 shows that relative to their respective peers, treated female students leave college with overall grade point averages that are 0.268 points higher than treated male students. This effect is nearly a "+" or "-" difference in overall GPA (e.g., a "B+" average of 3.3

versus a "B" average of 3.0).[15] Column (2) adds control variables that capture the demographics and characteristics of students' originating locations. The results are nearly unchanged. Columns (3) and (4) examine *Timely degree* as the dependent variable, which is an indicator taking a value of one if the student receives a degree by 2017, and zero otherwise. Results show that treated female students are more likely than treated male students to graduate from college as of 2017.

In Table 7, we explore whether financial shocks differentially affect students' career paths post college – in particular, the likelihood that treated males and females enter careers in finance / business or management. Existing studies show that females remain underrepresented in business- and management-related careers; e.g., Adams and Kirchmaier (2016), Hoff et al. (2024), McKinsey & Company (2024). A recent study by Hampole, Truffa, and Wong (2024) finds that this gender gap is reduced by women's exposure to female peers in early life. Specifically, a larger share of female peers during their MBA study significantly increases women's advancement into senior management positions.[16]

A student's decision to pursue finance / business career may likewise be influenced by the early life exposure to financial circumstances. The experience of family financial shocks may accentuate the importance of financial decisions, thereby encouraging students to pursue a finance career and achieve financial sophistication. To the extent that female students manage to outperform male students and exhibit greater perseverance in college enrollment following financial shocks, we examine whether these shocks differentially affect males' and females' finance / business career paths, and whether this effect varies with family financial resources.

[Insert Table 7 here.]

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[15] The average college GPA of our sample students is 3.04, and 81% have received a degree by 2017.

[16] Relatedly, Bostwick and Weinberg (2018) find that female peers help women persist and excel in doctoral STEM programs. Adams, Barber, and Odean (2018) find that having a STEM mother increases females' probability of becoming CFA Institute members, indicating the influence of female role models in career choice.

Table 7 presents the results. The dependent variable in columns (1) to (2) is *Finance / Business career*, an indicator variable taking the value of one if the student takes a job in finance- or business-related industry after leaving college, and zero if the student takes a job in another industry. BPS12 provides the six-digit code of a student's occupation category as of 2017, based on the classification of the U.S. Bureau of Labor Statistics (BLS). Occupation information is available for about 76% of our sample students. A finance / business occupation is one in the category of 13-0000, and it accounts for approximately 7% of our sample observations. The negative coefficients of *Female* suggest that overall (in the absence of financial shocks), female students are less likely to take finance / business career than male students – echoing the underrepresentation of female in these occupations. However, the positive coefficients of *Treated* × *Female* in column (1) indicate that financial shocks during college can mitigate this underrepresentation – and for students from low-earning families, financial shocks make female students more likely to purse finance / business career than their female peers. The economic magnitude of *Treated* × *Female* is sizable, although statistically significant at 10% level, likely due to the limited sample size.

We do not observe such an effect among students from high-earning families. In column (2), the coefficient of *Female* is negative and significant – suggesting that female's underrepresentation in finance / business is particularly pronounced in this group. This observation is perhaps unsurprising because men from these families may have a greater advantage in leveraging the wealth and networks to advance into finance and business careers. In this case, financial shocks do not significantly help females reduce the underrepresentation, as shown by the insignificant coefficient of *Treated* × *Female*.

In columns (3) and (4), we perform a similar analysis on student's career in management occupations. A management occupation is one in the category of 11-0000 classified by the BLS and it accounts for about 8% of our sample. Besides senior managers (top executives), the 11-0000 category broadly includes operations managers, sales managers, and healthcare managers, among others. We are not able to focus on senior management positions, as in Hampole et al. (2024), because in our sample, such positions are associated with a limited number of observations. The insignificant coefficients of *Treated* × *Female* in columns (3) and (4) suggest that financial shocks do not help female students advance into management positions relative to their control peers.

6. Plausible explanations for the gender gap reversal

6.1. The role of self-efficacy

Kuhnen and Melzer (2018) show that individuals with high self-efficacy – i.e., belief that their actions or effort can influence future outcomes – navigate financial shocks better than those with low self-efficacy. Greater self-efficacy eventually leads to healthier financial standing and lower financial distress, and this effect is more prominent for individuals from poorer families. We hypothesize that this noncognitive attribute plays a role in our documented gender gap reversal in course performance and college enrollment following financial shocks.[17]

The conceptual framework underlying this hypothesis follows Kuhnen and Melzer (2018). Self-efficacy influences an individual's perception of benefits from exerting effort. In the presence of financial shocks, a student decides whether to exert costly effort (such as studying longer hours) in response to the adverse circumstances. A student with high self-efficacy may perceive a larger marginal benefit from her effort, and thus is more willing to make such sacrifice. In contrast, a student with low self-efficacy may find limited potential in turning around adversity and thus accept a worse outcome.

We examine this role of self-efficacy by performing a cross-sectional test. We utilize prior evidence that the academic self-efficacy of males and females varies across subject matter. Females

[17] This hypothesis is also in line with existing studies documenting a positive relation between self-efficacy and academic performance, education attainment, and labor market outcomes (e.g., Lindqvist and Vestman, 2011; Heckman, Pinto, and Savelyev, 2013)

exhibit higher self-efficacy in language arts or writing but are found to lack self-efficacy relative to males in mathematics, engineering, and computer science (STEM fields); e.g. Huang (2013) and Burger et al. (2010).[18] Without believing that action can sufficiently change their performance in STEM fields, females may be discouraged from exerting costly effort during the financial shocks in STEM courses. With stronger self-efficacy in STEM fields, males may be more willing to make sacrifices to combat the adversity in these fields. In either case, females' average outperformance over males would be muted in the subsample of STEM courses and if so, we can infer that self-efficacy plays an important role in explaining the baseline gender gap reversal. This is indeed what we find in Table 8.

[Insert Table 8 here.]

Table 8 performs our DDD analysis in Table 3 among STEM courses and non-STEM courses separately. BPS12 identifies STEM courses based on three sources: the Science, Mathematics and Research for Transformation (SMART) Scholarship, the National Science Foundation (NSF), and the National Center for Education Statistics (NCES). Columns (1) and (2) present the results using STEM courses identified by SMART. We observe a sharp contrast. Among STEM courses, treated male students see lower, but insignificant, grades than male controls following the shock, as captured by the coefficient of *Treated* × *Post* (-0.249). The summation of the coefficients of *Treated* × *Post* and *Treated* × *Post* × *Female* is -0.087 (=-0.249+0.162), suggesting that in STEM courses, female students likewise experience lowered grades than female controls, albeit insignificantly. As such, females neither outperform nor underperform males in STEM courses. In STEM fields, the absence of children and family obligations nullifies the gender-based performance gap documented in the motivating literature.

[18] In a similar spirit, Brenøe, A. A. and U. Zölitz (2020) find that exposure to more female peers lowers women's probability of participating in and graduating from STEM programs. This effect reduces females' STEM occupation take up and earnings in the long run.

Females' significant outperformance is observed only in non-STEM courses, as seen in column (2). There, treated male students significantly underperform their male peers (i.e., *Treated* × *Post* = -0.552, significant at the 1% level), whereas treated female students continue to perform similarly as the controls following the shocks. As such, females outperform males by 0.6 notches of grades in non-STEM fields.

Columns (3) and (4) use a more stringent definition for STEM, in which all three sources need to unanimously identify a course as STEM (and a course is identified as non-STEM if any of the sources classifies otherwise). The results are similar. Taken together, these results lend support to our hypothesis that self-efficacy plays an important role in explaining the gender gap reversal.

We cannot rule out the alternative explanation that the two subsamples of courses capture gendered differences in students' *abilities* to handle STEM. If females, by chance, are less proficient in mastering STEM materials, then their outperformance over males would similarly diminish in these courses – confounding our hypothesis regarding self-efficacy. We note that one prediction unique to the self-efficacy hypothesis is that high-self efficacy individuals should exhibit more effort and perseverance upon encountering shocks, as they believe that actions can change adversity – and this prediction is supported by our finding that females remain enrolled in college following the shocks, whereas males drop out (Section 5.4).

6.2. Is there a gender gap in compensating mechanisms?

We next examine a few alternative explanations. We first consider whether males and females differ in their approaches to addressing the unexpected financial constraints, e.g., by taking part-time jobs – and whether these different approaches result in variation in academic performances. Figure A2 in the Online Appendix presents part-time job take up for male and female students. We perform a similar analysis as in Figure 2, with part-time employment as the outcome variable (i.e., the logarithm of one plus the number of weekly employment hours at part-time jobs). That is, we trace how treated student *A* and control students *B* change their part-time job employment surrounding the shock. Because part-time job information is available annually, this analysis is performed in an annual panel.

Figure A2 shows that treated and control female students have no significant difference in part-time job hours prior to financial shocks. Further, differences in their part-time job hours remain insignificant after the shocks. We observe a different response for males. Treated and control male students work similar hours in the pre-shock years. However, treated male students work significantly more hours in the year of the shock relative to control male students, and the effect persists through the following two years.

These comparisons indicate that male students compensate differently in response to financial shocks than female students by working more hours. The largest point estimate for treated male students relative to control male students in Figure A2 is about 1.6. This magnitude translates to approximately five additional hours of part-time work per week. This effect is nontrivial. However, working five additional hours per week may not be sufficiently disruptive to generate the performance gender gaps in Figure 2 and Tables 3 and 6, namely, that treated female students earn about 1.5 notches higher course grades than males, and are over ten percent more likely to finish college in a timely manner. Nevertheless, we formally test whether part-time job take-up can explain the gender performance gap we observe due to financial shocks.

To do so, we augment Equation (2) by including an additional triple-interaction term in the regression: *Treated* × *Post* × *Job* (along with other pair-wise interactions and the standalone indicators). This specification additionally controls for students' part-time job take-up. If treated male students' part-time jobs explain why they earn lower course grades after financial shocks relative to treated female students, then the coefficient of *Treated* × *Post* × *Job* should be negative and statistically significant, and it should subsume the original coefficient of *Treated* × *Post* × *Female.* We use two proxies for part-time job take-up. *Job dummy* is an indicator taking a value of one if the student works any part-time hours during the academic year. *Job hours* is the logarithm of one plus the average weekly number of hours the student works in part-time jobs in the academic year (the hours equal zero if the student does not take any part-time jobs). Table 9 shows the results.

[Insert Table 9 here.]

Columns (1) and (2) of Table 9 show that part-time job take-up does not explain the gender performance gap in course performance generated by financial shocks. The coefficients of *Treated* × *Post* × *Female* remain economically large and statistically significant while the coefficients of *Treated* × *Post* × *Job* are insignificant. Columns (3) and (4) likewise show that part-time job hours do not explain the gender performance gap. Overall, we conclude that although males compensate more for financial shocks by working part-time than females, this behavior cannot fully explain the gender performance gap that is generated by financial shocks.

Relatedly, we examine whether male and female students differ in borrowing behavior after financial shocks. The existing literature documents that student loan indebtedness causes significant negative impact on borrowers' personal and professional lives.[19] The anticipation of such negative impact may create a psychological burden and adversely affect students' academic performances. If males tend to borrow more student debt than females following the shocks, then this difference may give rise to the gender gap reversal.

Figure A3 in the Online Appendix traces how treated student *A* and control students *B* change student debt borrowing surrounding the shock – in which the outcome variable is the logarithm of one plus the total amount of federal student loans borrowed by a student in each year. We find that the borrowing behavior is similar for both genders, suggesting that it is unlikely to drive the gender gap reversal observed in our baseline results. Indeed, in untabulated analyses, we

[19] The impact includes reduced small business formation and entrepreneurship (Amromin and McGranahan 2015; Krishnan and Wang 2019), delayed homeownership and family formation (Gicheva 2011; Cooper and Wang 2014; Mezza, Ringo, Sherlund, and Sommer 2016; Goodman, Isen, and Yannelis. 2021), lower graduate school enrollment (Chakrabarti, Fos, Liberman, and Yannelis 2023), reduced stock market participation (Batkeyev, Krishnan, and Nandy 2017), and suboptimal labor market outcomes or human capital decisions (Minicozzi 2005; Rothstein and Rouse 2011; Weidner 2016; Lou and Mongey 2019; Ji 2021; Hampole 2023).

perform a similar test as in Table 9, including the additional triple interaction term *Treated* × *Post* × *Student loan amount*. We obtain the same conclusion.

6.3. Is there a gender gap in mental health?

We next test whether males and females have similar responses to financial shocks in terms of their mental health. If males are particularly distressed, then this could explain why they earn lower course grades than females. We measure changes in mental health around financial shocks with the five-point scale classified by the BPS survey. The highest value, 5, indicates students have excellent mental health, while the lowest value, 1, indicates poor mental health. *Mental status change* is the within-student change in this value around financial shocks. This variable, however, is not surveyed annually, but only three times: at the end of their first year, and then three and six years later. If the shock happens between 2012 and 2014, the mental health change is calculated as the difference between a student's mental health status in 2014 and 2012; if the shock happens between 2014 and 2017, then it is the difference between mental status in 2014 and 2017. We require observations both before and after financial shocks for this analysis, with the caveat that the timing of observations from the BPS survey may not be symmetric around the timing of financial shocks. A lower value of the dependent variable indicates deterioration in mental health. We begin by estimating the following OLS regression:

$$Mental\ Status\ change_i = \alpha + \beta_1 \times Treated_i + \beta_2 \times Student\ and\ Family\ Charateristics_i + Fixed\ Effects + \varepsilon. \qquad (5)$$

This regression tests whether treated students, both male and female, experience changes in their mental health around financial shocks. Similar to Equation (4), we include *Course-semester* × *Fam. state* fixed effects, which force comparison between treated and control students enrolled in the same course at the same time and originating from the same home state.

Column (1) in Table 10 shows that β_1 is statistically significant with a point estimate of -0.520. The result indicates that treated students experience an average reduction in mental health of more than ten percent of the entire range of mental health responses following financial shocks. This effect remains robust in column (2) with additional control variables.

[Insert Table 10 here.]

Columns (3) and (4) augment Equation (5) by including the interaction of the *Treated* with an indicator for gender. This approach tests whether the deterioration in mental health following financial shocks established in columns (1) and (2) varies by gender. It does not. Males and females exhibit equal deterioration in mental health following financial shocks. Therefore, changes in mental health are unlikely to explain the gender gap in performance due to financial shocks.

6.4. Are male students spuriously treated with stronger natural disasters?

The gender gap we uncover indicates that males perform worse in response to financial shocks than females. This gap could arise spuriously if the family financial resources of male students are, by chance, hit by stronger natural disasters. We examine this possibility by investigating the changes in family financial conditions for female and male students, respectively around natural disasters. That is, we repeat the Figure 1 analyses separately among female and male students. Figure 4 plots the results.[20]

[Insert Figure 4 here.]

The results show that treated and control female students have no significant differences in family income (proxied by tax paid) or earnings prior to the disasters. Reductions in family income and earnings affect both treated males and females in a similar magnitude, although the timing of the effect varies. For females, the effect is significant in the year of the disaster. For males it is significant in the year after. Comparing the reductions in resources across panels, the magnitudes of the effects are similar between males and females. Therefore, we conclude that our results do not reflect a spurious relation driven by male students' greater exposure to treatment effects.

[20] Due to missing values of parental savings, we repeat the analyses using total income (tax paid) and earnings.

7. Conclusion

Recent studies document that female professionals exhibit greater productivity losses relative to their male peers in the face of productivity shock. In a setting without confounding effects of children or family responsibilities, we document a complete reversal in that expected gender performance gap following financial shocks.

Using colleges as a laboratory and natural disasters as plausibly exogenous shocks to family finances, we find that males whose families experience deteriorating financial conditions underperform their male classmates who do not experience such shocks; in contrast, affected female students continue to perform similarly as their peers. This gender gap reversal is present for white and non-white students. It is more prominent when students' families are poorer ex ante. The gender gap reversal is not the result of a selection effect, whereby females discontinue college enrollment at higher rates than males to protect their GPAs. Not only do males earn lower grades, they also respond to financial shocks by becoming more likely to drop out of college. The gender gap also manifests in the long run, as males who experience financial shocks are more likely to exit college with lower GPAs and take longer to finish their degrees, whereas females do not exhibit these adverse outcomes. In fact, females become more likely to have careers in industries such as business or finance following the shock than otherwise.

We provide evidence that self-efficacy plays a role in the baseline gender gap reversal. We bifurcate analyses based on STEM fields (where males exhibit greater self-efficacy) and non-STEM fields (where women exhibit greater self-efficacy). We find that the gender gap reversal nullifies male overperformance in STEM fields; women perform neither better nor worse than men in STEM courses following the financial shock. Among non-STEM fields, women outperform men, on average.

Although males mitigate financial shocks by taking more part-time jobs and working more hours during college than females, this difference in working behavior does not explain the gender gap reversal. We find treated male and female students show similar deteriorations in mental health following financial shocks, and their families experience similar financial shocks from natural disasters on average, indicating our results are not attributable to differences in mental responses to shocks, or spuriously driven by males' families receiving stronger treatment effects on average. Overall, we conclude that females exhibit greater resilience in their human capital investment following adverse financial shocks.

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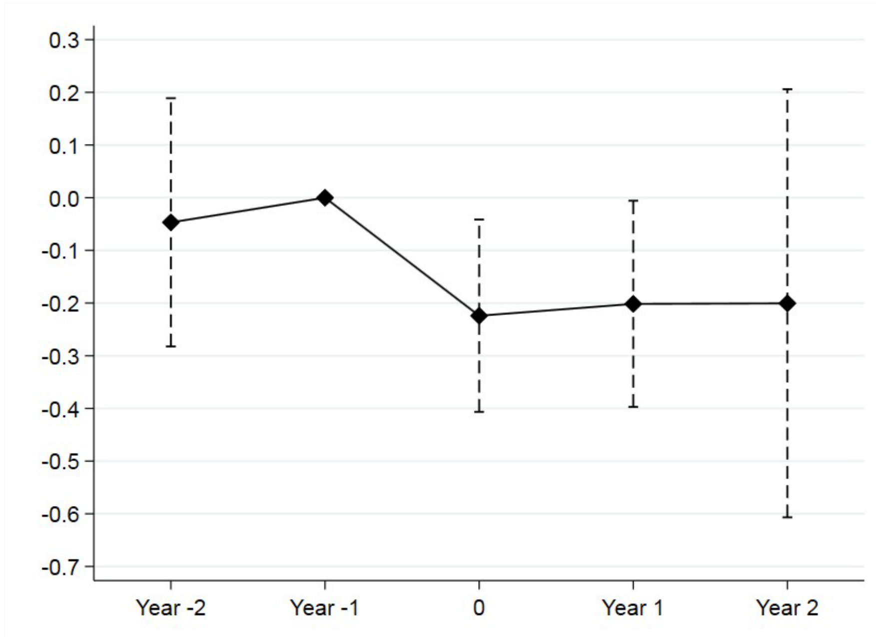
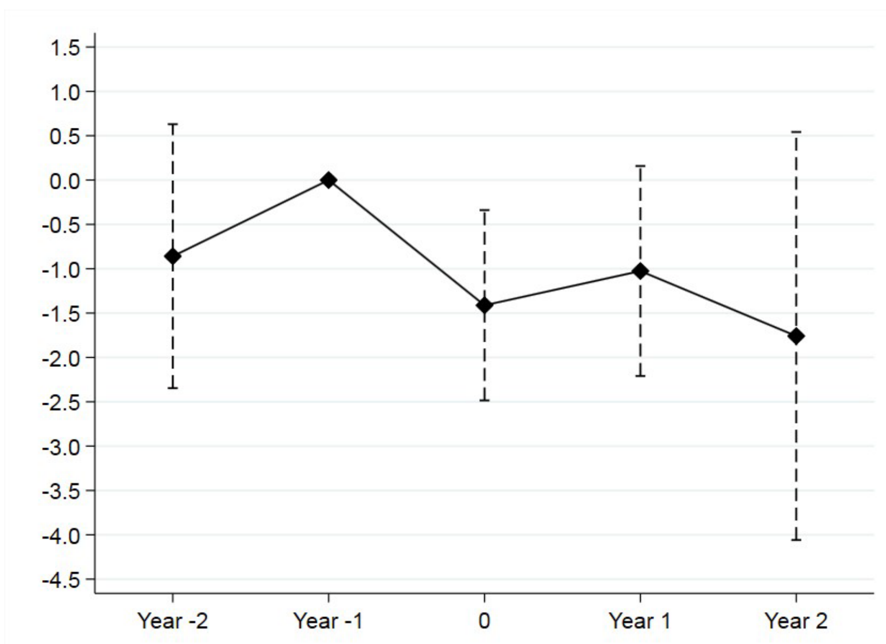
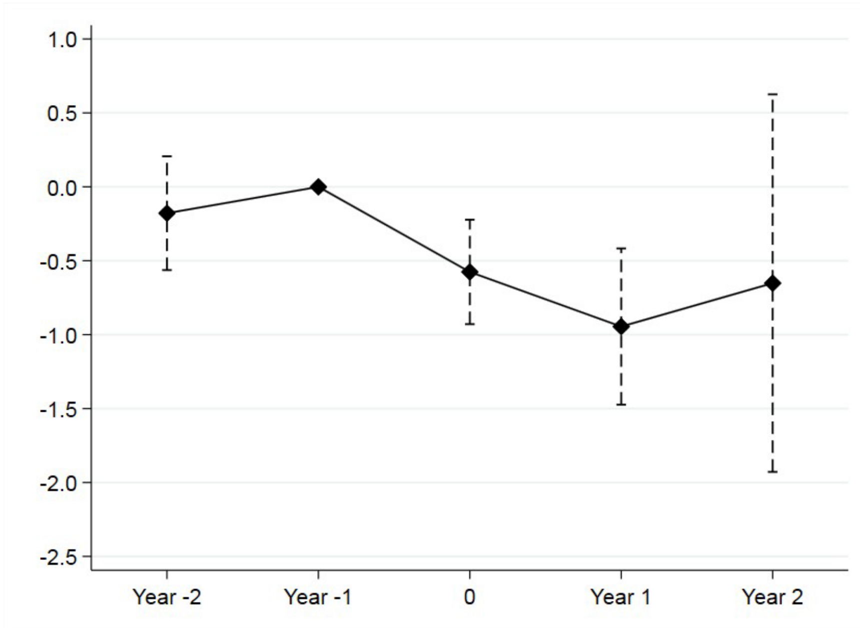
Panel A. Taxes paid (proxy for total income)



Panel B. Earnings



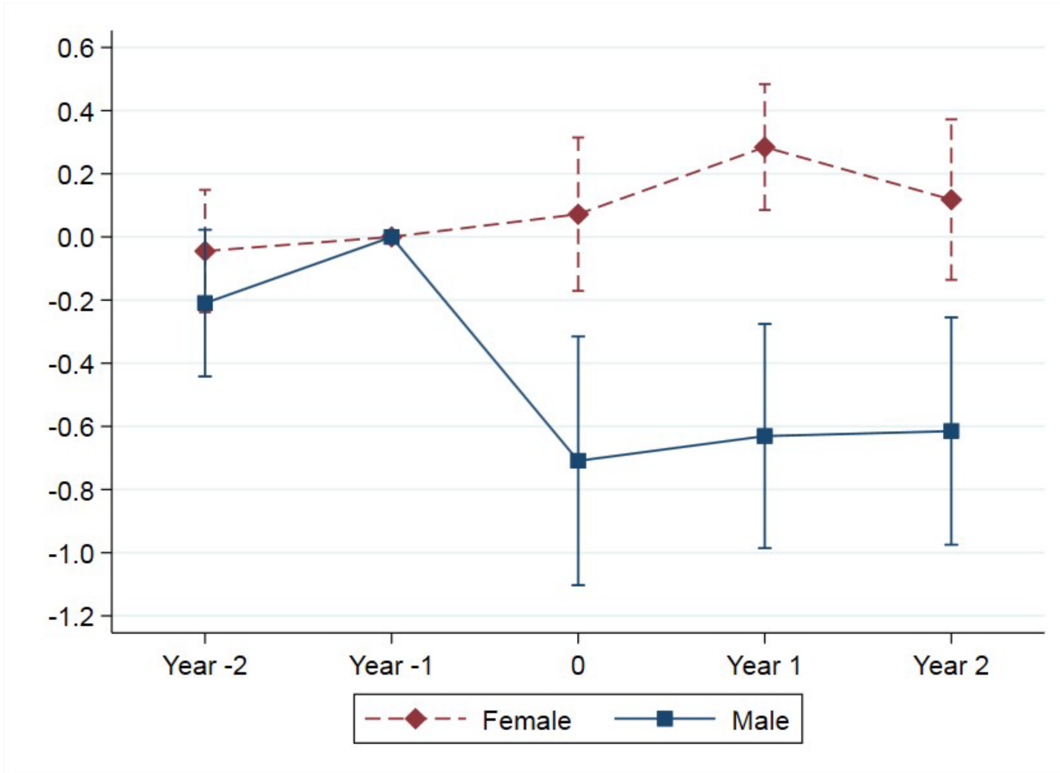
Panel C. Savings



SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).
NOTE: Estimates are weighted based on survey weights for panel analysis.

Fig. 1. Validation of the effect of disruptive disasters on family financial conditions.

This figure validates that, on average, disruptive disasters create financial shocks to students' parents, as reflected in parental total income (proxied by total tax paid), earnings, and savings. Disruptive disasters are identified following the procedure described in Section 4. For each student A who experiences a family shock when enrolled in course during a semester, we assign control students who are enrolled in the same course at the same university during the same semester but do not experience the shocks at that time. Then we track these treated-control students' parental financial conditions over event time. This figure plots the coefficients of the interaction between *Treated* and event time indicators, estimated from the difference-in-differences model in Section 5.1. The coefficient estimations are reported in Table A1. Time 0 denotes the year-end when the disaster happens. Year -1 (or Year 1) denotes the year end before (or after) the disaster year, and Year -2 (or Year 2) denotes the second year end before (or after) time 0. The bars surrounding each coefficient represent the two-sided 90% confidence intervals.

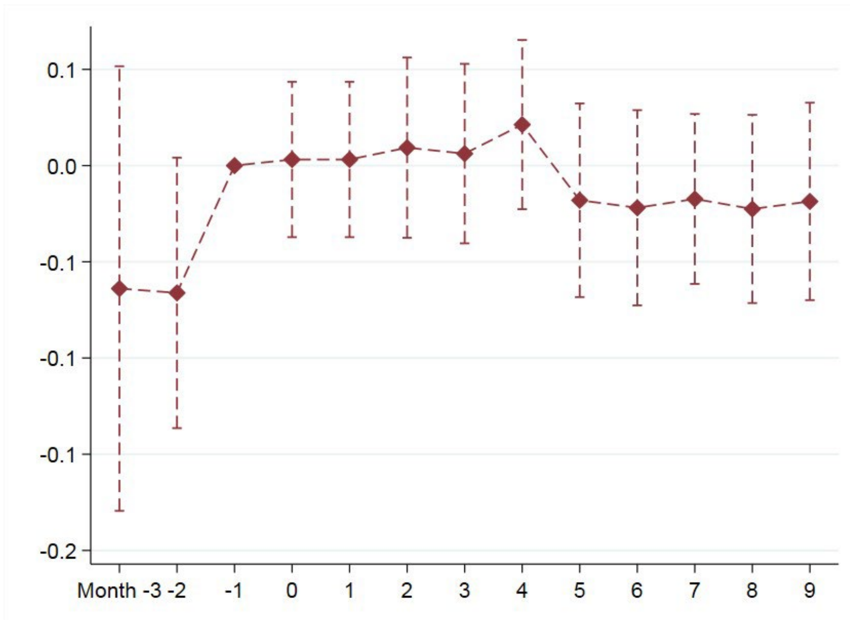


SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).
NOTE: Estimates are weighted based on survey weights for panel analysis.

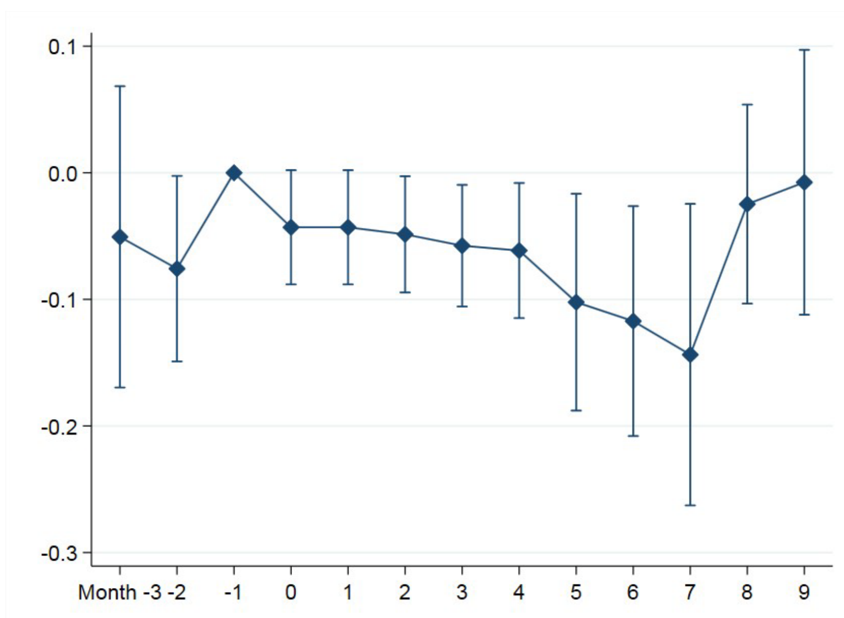
Fig. 2. Dynamics of course grades over event time for female and male students.

This figure plots the coefficients of the interaction between *Treated* and event time to analyze students' course performances over event time relative to the control students, separately for female (the dashed line) and male students (the solid line). Time 0 denotes the semester when a student experiences the family financial shock. To plot the dashed line, for each female treated student A who experiences a family shock when enrolled in course X during a semester (i.e., time 0), we assign female control students who are enrolled in the same course X at the same university during the same semester but do not experience the shocks at that time. Then we look for courses Y that treated student A is enrolled in before and after time 0, and assign student A with female control students contemporaneously enrolled in Y. We compare the grades of these female treated and control students given each course. If course Y occurs in a semester within one year before (or after) the semester when student A experiences a family shock (time 0), then it is included in the sample of Year -1 (or Year 1). If course Y occurs in a semester between one year and two years before (or after) time 0, then it is included in the sample of Year -2 (or Year 2). The year prior to the shock (i.e., -1 year) is omitted as the baseline. To plot the solid line, we perform the same analyses among male students. The detailed regression specification is discussed in Section 5.2. The dashed line presents a difference-in-difference estimation among female students, and the solid line presents a difference-in-difference estimation among male students. The contrast between the two lines presents a triple-difference estimation. The bars surrounding each coefficient represent the two-sided 90% confidence intervals.

Panel A. Female students



Panel B. Male students

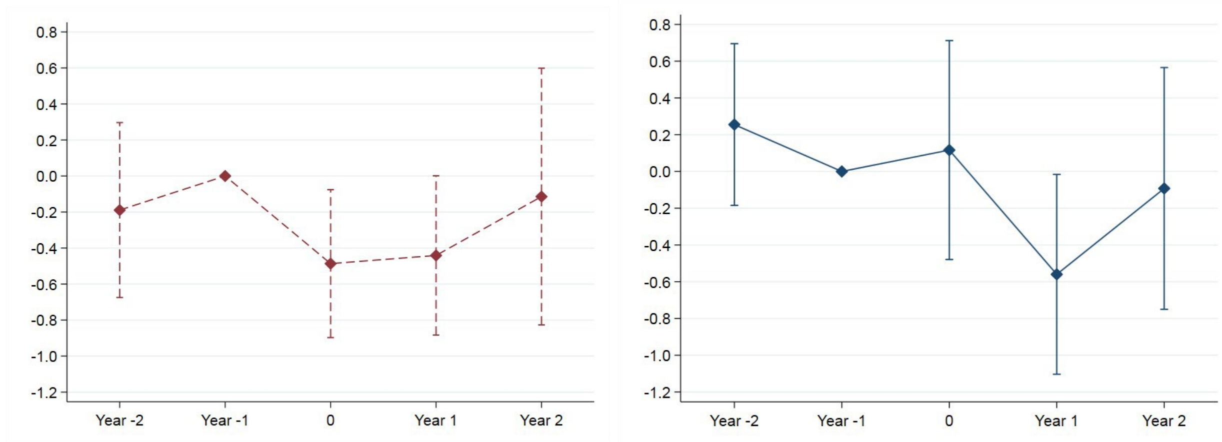


SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).
NOTE: Estimates are weighted based on survey weights for panel analysis.

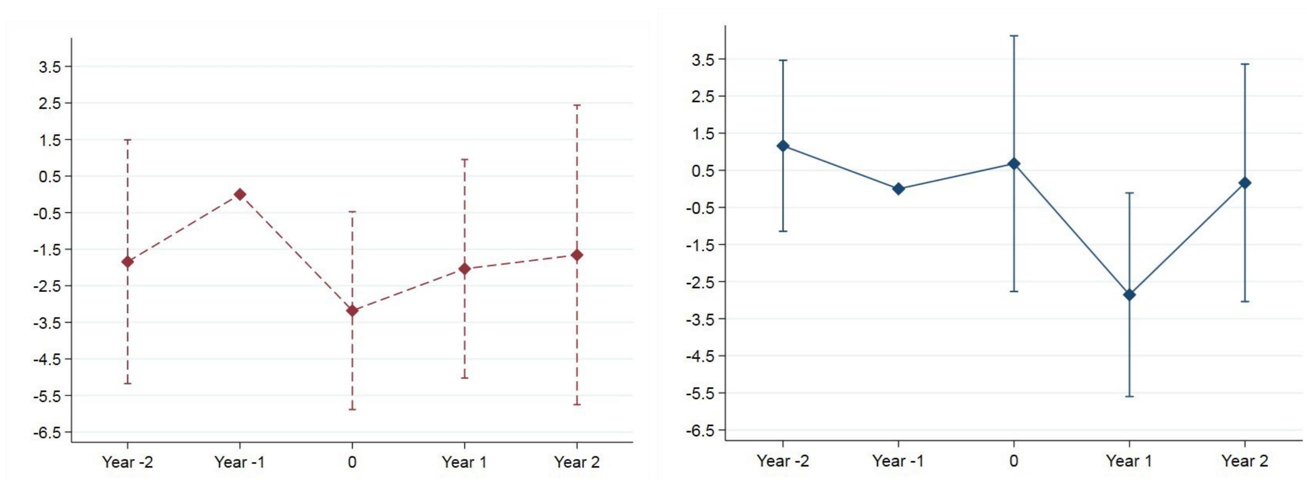
Fig. 3. Dynamics of enrollment continuation over event time for female and male students.

This figure plots the coefficients of the interaction between *Treated* and event time to analyze students' monthly enrollment over event time relative to the control students, separately for female (the dashed line) and male students (the solid line). Time 0 denotes the month when a student experiences the family financial shock. To plot the dashed line, for each female treated student A who experiences a family shock when enrolled in course X during a semester, we assign female control students who are contemporaneously enrolled in the same course X at the same university but do not experience the shocks at that time. Then we track the monthly enrollment of these female treated and control students over time from three months before the month of shock (denoted as month -3) to nine months after (denoted as month 9). Enrollment is captured by an indicator that equals one if a student is enrolled in college in a month and zero otherwise. The month prior to the month of shock (i.e., month -1) is omitted as the baseline. To plot the solid line, we perform the same analyses among male students. The detailed regression specification is discussed in Section 5.4. The dashed line presents a difference-in-difference estimation among female students, and the solid line presents a difference-in-difference estimation among male students. The contrast between the two lines presents a triple-difference estimation. The bars surrounding each coefficient represent the two-sided 90% confidence intervals.

Panel A. Taxes paid (proxy for total income)



Panel B. Earnings



SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).
NOTE: Estimates are weighted based on survey weights for panel analysis.

Fig. 4. Changes in family financial conditions for female and male students.

This figure repeats analyses in Figure 2 to examine how disruptive disasters affect family financial conditions, separately for female and male students. Financial conditions are captured by parental total income (tax paid) in Panel A and earnings in Panel B. The dashed lines include the families of female students, and the solid lines include the families of male students. Sample and regression specifications are the same as in Figure 2. The bars surrounding each coefficient represent the two-sided 90% confidence intervals.

Table 1. Summary statistics of disasters.

This table provides summary statistics of federally declared major natural disasters included in the subsequent analyses. Disasters are obtained from the Federal Emergency Management Agency (FEMA). Panel A provides summary statistics about the total cost of damage caused by disasters and the duration of disasters by type. Damage cost consists of public and personal damage cost. Public damage cost is obtained from the dataset Public Assistance Funded Projects Details from FEMA. This dataset includes information on the amount of federal grant for Public Assistance (PA) projects. The cost of public damage caused by a given disaster is the sum of the federal grant for all PA projects associated with this disaster. Personal damage cost is obtained from the dataset Individuals and Households Program - Valid Registrations from FEMA. This dataset contains applicant-level data for the Individuals and Households Program (IHP). For each applicant of the IHP assistance, the dataset includes information on the FEMA-determined value of disaster-caused damage to the applicant's real property components and personal property components. The cost of personal damage caused by a given disaster is the sum of the real property and personal property damage for all registered applicants associated with this disaster. The duration of a disaster is the number of days from the starting date to the ending date of the federal declaration. Panel B provides summary statistics at the disaster-county level for treated students. The first three columns of Panel B report disasters' total damage cost, public damage cost, personal damage cost, the number of applicants registering for federal assistance, and the duration for our sample disasters. In comparison, the last three columns of Panel B provide statistics for Hurricane Harvey between August 23, 2017 and September 15, 2017. The last two rows of Panel B report the number of disasters experienced by the overall sample students and by the treated students, respectively.

Panel A: Summary statistics of disasters for analyses

	Damage cost ($M)		Duration (Days)	
	Mean	Median	Mean	Median
Severe Storm	85.426	40.060	11.130	9.000
Flood	195.349	89.507	19.412	19.000
Hurricane	1,524.032	141.468	10.938	11.500
Others (Fire, Earthquake, Snow, Mud/Landslide)	49.018	41.876	37.714	14.000

Panel B: Summary statistics at the student (disaster-county) level

	Sample disasters			Recent major disaster (Hurricane Harvey)		
	Mean	Median	S.D.	Mean	Median	S.D.
Damage cost ($M)	173.718	8.990	865.477	110.927	22.489	347.795
Public damage cost ($M)	143.413	5.199	825.070	62.945	20.205	179.400
Personal damage cost ($M)	30.305	1.370	100.619	47.982	2.543	170.362
No. of applicant registrations	8,501.354	911.000	19,683.543	17,818.480	1,962.000	64,311.993
Duration (Days)	24.160	13.000	30.080	24.000	24.000	0.000
Avg. Number of disasters experienced (conditional)	1.209	1.000	0.407			
Avg. Number of disasters experienced (unconditional)	0.470	0.000	0.641			

SOURCE: U.S. Federal Emergency Management Agency (FEMA).

Table 2. Summary statistics of student and family characteristics.

This table provides summary statistics of key characteristics of students and families. The sample is based on financially dependent students with available college transcript information from the BPS12 database. For each student who experiences a family shock during a semester between academic years 2012 and 2018, we assign control students who are enrolled in the same course at the same university during the same semester but do not experience family shocks at that time. Family shocks are based on whether a student's parents are located in a county that experiences a disruptive natural disaster during the semester. Disruptive disasters are identified following the procedure described in Section 4. *Female*, *White*, and *Age* indicate students' gender, ethnicity, and age at the time of college enrollment, respectively. *SAT* indicates students' SAT composite scores. *Parents' college degree* is an indicator variable that equals one if a student's parents have earned a bachelor's degree or higher, and zero otherwise. *Parents' total tax paid* is the natural logarithm of one plus the amount of federal taxes a student's parents paid. *Parents' earnings* is the natural logarithm of one plus the amount of a student's parental gross income. *Parents' saving* is the natural logarithm of one plus the amount of a student's parental savings. Parental financial information is from the Free Application for Federal Student Aid (FAFSA) forms that students file immediately prior to the academic year of a family shock. *Number in college* is the number of children of a student's parents currently enrolled in college. *Confidence* is a dummy variable that equals one if a student agrees or strongly agrees the BPS12 survey question at the end of the first year of enrollment: "I am confident I have the ability to succeed as a student", and the student's average college GPA is or below 2.24 (i.e., grade C or below for most classes). *Non-traditional index* is the total number of non-traditional factors exhibited by a student categorized by the IES, including delayed enrollment, absence of high school diploma, part-time enrollment, single parent status, financially independent, having dependents, and working full time while enrolled. The table reports the characteristics for *Treated*=0 and *Treated*=1, among female and male students, respectively. Differences in means between the subsamples are also reported. Standard errors clustered at the student origin county and student level are in parentheses. Per IES restricted-use guidelines, all sample sizes are rounded to the nearest 10.

	Female						Male				
	Treated=0		Treated=1				Treated=0		Treated=1		
	N	Mean	N	Mean	Diff in Mean		N	Mean	N	Mean	Diff in Mean
White (0, 1)	2,210	0.677	1,100	0.629	-0.047		1,540	0.710	750	0.675	-0.035
					(0.042)						(0.052)
Age	2,210	18.244	1,100	18.333	0.089*		1,540	18.390	750	18.345	-0.045
					(0.046)						(0.065)
SAT	2,160	1,085.024	1,080	1,077.684	-7.340		1,480	1,110.721	740	1,111.809	1.088
					(15.938)						(22.695)
Parents' college degree (0, 1)	2,190	0.347	1,100	0.360	0.013		1,530	0.368	750	0.395	0.027
					(0.042)						(0.050)
Parents' total tax paid (log $)	1,730	6.885	790	7.123	0.238		1,140	6.927	560	6.836	-0.091
(Proxy for total income)					(0.352)						(0.535)
Parents' earnings (log $)	1,780	11.094	800	11.086	-0.008		1,170	11.082	590	11.094	0.011
					(0.091)						(0.118)
Parents' savings (log $)	1,130	7.050	560	6.740	-0.311		720	7.470	360	7.108	-0.362
					(0.504)						(0.635)
Number in college	1,820	1.413	830	1.502	0.088		1,200	1.420	590	1.376	-0.044
					(0.074)						(0.061)
Overconfidence (0, 1)	2,170	0.064	1,090	0.052	-0.013		1,470	0.085	730	0.092	0.007
					(0.019)						(0.029)
Non-traditional index	2,210	0.134	1,100	0.180	0.047		1,540	0.182	750	0.144	-0.039
					(0.045)						(0.043)

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).
NOTE: Estimates are weighted based on survey weights for panel analysis.

Table 3. Family financial shocks and academic performance of female and male students.

This table reports triple-difference regression analyses of the effect of family shocks on the course performance of female and male students. The dependent variable is a student's normalized transcript grade for the course. The sample is based on financially dependent students with available college transcript information from the BPS12 database. Students are excluded from the sample if their expected family contribution (EFC) is zero for the semester when disasters happen. For each treated student A who experiences a family financial shock when enrolled in course X during a semester between academic years 2012 and 2018, we assign control students who are enrolled in the same course X at the same university during the same semester but do not experience family shocks at that time. Then we look for courses Y that treated student A is enrolled in before and after the semester of shock, and assign student A with control students that are contemporaneously enrolled in Y. We compare the grades of these treated and control students in each course. Family shocks are based on whether a student's parents are located in a county that experiences a disruptive natural disaster during the semester. *Treated* indicates whether a student experiences family shocks or not. *Post* is an indicate that equals one if a course occurs during the semester of shock or in the two years after the semester of shock; it equals zero if a course occurs in the two years before the semester of shock. *Female* is an indicate for female students. *Fam. income* is the logarithm of one plus median family income of the census tract where a student's parents are located. *Pct. unemployed* is the percentage of unemployment in the census tract where a student's parents are located. *Pct. white* is the percentage of white population in the census tract where a student's parents are located. *Field of study FE* are indicators for each field of study classified by the two-digit Classification of Instructional Programs codes. All other variables are defined in Table 2. Interactions between event time indicators and control variables are included but not reported. Columns (4) and (5) repeat the analyses for white and non-white students separately. Robust standard errors (Taylor-series linearization) clustered at the student origin county and student level are in parentheses. ***, **, and * indicate coefficients significantly different from 0 at the 1%, 5%, and 10% levels, respectively. Per IES restricted-use guidelines, all sample sizes are rounded to the nearest 10.

Dependent variable: Course grades

	Overall			White	Non-white
	(1)	(2)	(3)	(4)	(5)
Treated × Post × Female	0.397**	0.430**	0.465**	0.603**	0.872*
	(0.196)	(0.218)	(0.220)	(0.286)	(0.488)
Treated × Post	-0.427***	-0.444**	-0.466**	-0.554**	-0.898**
	(0.144)	(0.185)	(0.188)	(0.234)	(0.392)
Treated × Female	-0.159	-0.133	-0.169	-0.308	-0.607
	(0.157)	(0.185)	(0.187)	(0.253)	(0.371)
Post × Female	-0.127	-0.095	-0.081	-0.074	-0.109
	(0.100)	(0.104)	(0.105)	(0.126)	(0.227)
Treated (0, 1)	0.185	0.030	0.052	0.203	0.339
	(0.118)	(0.153)	(0.156)	(0.207)	(0.232)
Female (0, 1)	0.195**	0.151*	0.132	0.013	0.595**
	(0.086)	(0.083)	(0.083)	(0.108)	(0.230)
White (0, 1)		0.221*	0.138	-	-
		(0.118)	(0.125)	-	-
Age		0.797	0.781	-0.399	1.557
		(1.297)	(1.301)	(1.425)	(2.842)
Parents' college degree		0.194**	0.194**	0.137	0.036
		(0.079)	(0.077)	(0.094)	(0.287)
Numcollege		0.030	0.034	0.017	-0.212
		(0.065)	(0.063)	(0.059)	(0.148)
Non-traditional index		-0.098	-0.096	-0.119	0.187
		(0.159)	(0.161)	(0.142)	(0.205)
Confidence (0, 1)		-0.523**	-0.532**	-0.499	-0.344
		(0.235)	(0.236)	(0.328)	(0.403)
SAT		1.202***	1.166***	1.355***	0.201
		(0.248)	(0.257)	(0.337)	(0.984)
Fam. income			-0.094	-0.040	-0.577**
			(0.114)	(0.136)	(0.281)
Pct. unemployed			0.004	0.006	-0.034
			(0.014)	(0.017)	(0.048)
Pct. white			0.006***	0.004	0.011
			(0.002)	(0.003)	(0.008)
Field of study FE	No	Yes	Yes	Yes	Yes
Course-semester × Fam. state × Event time FE	Yes	Yes	Yes	Yes	Yes
Observations	21,890	18,700	18,700	14,970	2,370
R-squared	0.471	0.530	0.533	0.523	0.719

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).
NOTE: Estimates are weighted based on survey weights for panel analysis.

Table 4. Heterogeneity by family financial conditions.

This table reports triple-difference regression analyses as in Table 3, separately for students from high- and low-income families. The dependent variable is a student's normalized transcript grade for the course. Family income is from the Free Application for Federal Student Aid (FAFSA) forms that students file immediately prior to the academic year of a family shock. Columns (1) and (2) include students with low parental earnings, and columns (3) and (4) include students with high parental earnings. High- (low-) parental earnings are those above (below) the medium of the sample distribution. The regression specification is the same as in column (3) of Table 3. Robust standard errors (Taylor-series linearization) clustered at the student origin county and student level are in parentheses. ***, **, and * indicate coefficients significantly different from 0 at the 1%, 5%, and 10% levels, respectively. Per IES restricted-use guidelines, all sample sizes are rounded to the nearest 10.

Dependent variable: Course grades

	Low parental earnings		High parental earnings	
	(1)	(2)	(3)	(4)
Treated × Post × Female	1.249***	1.251***	0.024	-0.002
	(0.396)	(0.383)	(0.233)	(0.217)
Treated × Post	-0.897***	-0.883***	-0.012	0.040
	(0.319)	(0.314)	(0.168)	(0.159)
Other interaction and standalone indicators	Yes	Yes	Yes	Yes
Student controls	Yes	Yes	Yes	Yes
Geo. demo. controls	No	Yes	No	Yes
Field of study FE	Yes	Yes	Yes	Yes
Course-semester × Fam. state × Event time FE	Yes	Yes	Yes	Yes
Observations	7,440	7,440	7,350	7,350
R-squared	0.550	0.564	0.692	0.696

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).
NOTE: Estimates are weighted based on survey weights for panel analysis.

Table 5. Family financial shocks and enrollment continuation of female and male students.

This table reports triple-difference regression analyses of the effect of family shocks on the continuation of college enrollment of female and male students. The dependent variable is an indicator for a student's monthly enrollment, which equals one if the student is enrolled in college and zero otherwise in a month. The sample is based on financially dependent students with available college transcript information from the BPS12 database. Students are excluded from the sample if their expected family contribution (EFC) is zero for the semester when disasters happen. For each treated student A who experiences a family financial shock when enrolled in course X during a semester between academic years 2012 and 2018, we assign control students who are contemporaneously enrolled in the same course X at the same university but do not experience family shocks at that time. Then we track the monthly enrollment of these female treated and control students over time from three months before the month of shock (denoted as month -3) to nine months after (denoted as month 9). The month of shock is denoted as time 0. The analyses are performed separately for students from high- and low-income families. Family income is from the Free Application for Federal Student Aid (FAFSA) forms that students file immediately prior to the academic year of a family shock. Columns (1) and (2) include students with low parental earnings, and columns (3) and (4) include students with high parental earnings. High- (low-) parental earnings are those above (below) the medium of the sample distribution. The regression specification is the same as in column (3) of Table 3. Robust standard errors (Taylor-series linearization) clustered at the student origin county and student level are in parentheses. ***, **, and * indicate coefficients significantly different from 0 at the 1%, 5%, and 10% levels, respectively. Per IES restricted-use guidelines, all sample sizes are rounded to the nearest 10.

Dependent variable: Enrollment	Low parental earnings		High parental earnings	
	(1)	(2)	(3)	(4)
Treated × Post × Female	0.164***	0.160***	-0.069	-0.086
	(0.051)	(0.052)	(0.058)	(0.059)
Treated × Post	-0.130***	-0.121**	0.094	0.111*
	(0.047)	(0.050)	(0.062)	(0.059)
Other interaction and standalone indicators	Yes	Yes	Yes	Yes
Student controls	Yes	Yes	Yes	Yes
Geo. demo. controls	No	Yes	No	Yes
Field of study FE	Yes	Yes	Yes	Yes
Course-semester × Fam. state × Event time FE	Yes	Yes	Yes	Yes
Observations	20,410	20,310	21,110	21,090
R-squared	0.425	0.426	0.382	0.382

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).
NOTE: Estimates are weighted based on survey weights for panel analysis.

Table 6. Students' long-term academic standing.

This table presents regression analyses of the effect of family shocks on students' academic standing at the conclusion of college. In columns (1) and (2), the dependent variable is student GPA throughout college. In columns (3) and (4), the dependent variable is an indicator for whether a student has received a degree as of 2017. For each treated student A who experiences a family financial shock when enrolled in course X during a semester between academic years 2012 and 2018, we assign control students who are contemporaneously enrolled in the same course X at the same university but do not experience family shocks at that time. Then we examine the college outcomes of these treated-control students. Robust standard errors (Taylor-series linearization) clustered at student origin county and student level are in parentheses. ***, **, and * indicate coefficients significantly different from 0 at the 1%, 5%, and 10% levels, respectively. Per IES restricted-use guidelines, all sample sizes are rounded to the nearest 10.

Dependent variables:	Overall GPA		Timely degree	
	(1)	(2)	(3)	(4)
Treated * Female	0.268**	0.277**	0.152**	0.139*
	(0.119)	(0.118)	(0.077)	(0.078)
Female	0.195**	0.195**	0.008	0.011
	(0.089)	(0.091)	(0.051)	(0.052)
Treated	-0.350***	-0.331***	-0.190***	-0.186***
	(0.112)	(0.113)	(0.065)	(0.067)
Student controls	Yes	Yes	Yes	Yes
Geo. demo. controls	No	Yes	No	Yes
Field of study FE	Yes	Yes	Yes	Yes
Course-semester × Fam. state FE	Yes	Yes	Yes	Yes
Observations	2,010	2,010	2,010	2,010
R-squared	0.663	0.672	0.694	0.696

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).
NOTE: Estimates are weighted based on survey weights for panel analysis.

Table 7. Students' career paths.

This table presents regression analyses of the effect of family shocks on students' career upon graduation. In columns (1) to (2), the dependent variable is an indicator for whether a student takes a finance / business occupation as of December 2017. A finance / business occupation is one in the category of 13-0000 classified by the U.S. Bureau of Labor Statistics (BLS). In columns (3) to (4), the dependent variable is an indicator for whether a student takes a management occupation as of December 2017. A management occupation is one in the category of 11-0000 classified by the U.S. Bureau of Labor Statistics (BLS). For each treated student A who experiences a family financial shock when enrolled in course X during a semester between academic years 2012 and 2018, we assign control students who are contemporaneously enrolled in the same course X at the same university but do not experience family shocks at that time. Then we examine the college outcomes of these treated-control students. We separately examine students from high- and low- parental earnings families, as classified in Table 4 and Table 5. Robust standard errors (Taylor-series linearization) clustered at student origin county and student level are in parentheses. ***, **, and * indicate coefficients significantly different from 0 at the 1%, 5%, and 10% levels, respectively. Per IES restricted-use guidelines, all sample sizes are rounded to the nearest 10.

Dependent variables:	Finance / business career		Management career	
	Low parental earnings	High parental earnings	Low parental earnings	High parental earnings
	(1)	(2)	(3)	(4)
Treated * Female	0.151*	0.014	0.038	0.053
	(0.079)	(0.070)	(0.132)	(0.164)
Female	-0.045	-0.139**	0.009	0.047
	(0.048)	(0.064)	(0.051)	(0.079)
Treated	-0.062	-0.011	0.059	-0.025
	(0.049)	(0.080)	(0.096)	(0.122)
Student controls	Yes	Yes	Yes	Yes
Geo. demo. controls	Yes	Yes	Yes	Yes
Field of study FE	Yes	Yes	Yes	Yes
Course-semester × Fam. state FE	Yes	Yes	Yes	Yes
Observations	580	510	580	510
R-squared	0.696	0.814	0.643	0.712

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).
NOTE: Estimates are weighted based on survey weights for panel analysis.

Table 8. The role of self-efficacy: STEM versus non-STEM courses.

This table reports triple-difference regression analyses as in Table 3, separately for STEM and non-STEM courses low-income families. The dependent variable is a student's normalized transcript grade for the course. In columns (1) and (2), STEM courses are classified based on the Science, Mathematics and Research for Transformation (SMART) Scholarship. In columns (3) and (4), STEM courses are the ones unanimously classified by three sources, SMART, the National Science Foundation (NSF), and the National Center for Education Statistics (NCES). The regression specification is the same as in column (3) of Table 3. Robust standard errors (Taylor-series linearization) clustered at the student origin county and student level are in parentheses. ***, **, and * indicate coefficients significantly different from 0 at the 1%, 5%, and 10% levels, respectively. Per IES restricted-use guidelines, all sample sizes are rounded to the nearest 10.

Dependent variable: Course grades

	SMART Grant		SMART Grant & NSF & NCES	
	Non-STEM courses	STEM courses	Non-STEM courses	STEM courses
	(1)	(2)	(3)	(4)
Treated × Post × Female	0.600***	0.162	0.600***	0.164
	(0.190)	(0.338)	(0.190)	(0.338)
Treated × Post	-0.552***	-0.249	-0.552***	-0.250
	(0.150)	(0.248)	(0.150)	(0.248)
Other interaction and standalone indicators	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Field of study FE	Yes	Yes	Yes	Yes
Course-semester × Fam. state × Event time FE	Yes	Yes	Yes	Yes
Observations	16,260	2,430	16,260	2,430
R-squared	0.535	0.595	0.535	0.595

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).
NOTE: Estimates are weighted based on survey weights for panel analysis.

Table 9. Alternative explanation – part-time job take-up.

This table examines whether the differential effects of family shocks on the course performance of female and male students are driven by part-time jobs. The dependent variable is a student's normalized transcript grade for the course. The sample and regression specification follow Table 3. We additionally include a triple interaction term as the independent variable that captures students' part-time job take-up. In columns (1) and (2), part-time job take-up is captured by *Job dummy*, an indicator for whether a student takes any part-time jobs in a given academic year. In columns (3) and (4), part-time job take-up is captured by *Job hours*, the logarithm of one plus the number of weekly employment hours at part-time jobs. Part-time jobs require fewer than 40 hours per week on average in an academic year. All other variables are defined as in Table 3. Robust standard errors (Taylor-series linearization) clustered at the student origin county and student level are in parentheses. ***, **, and * indicate coefficients significantly different from 0 at the 1%, 5%, and 10% levels, respectively. Per IES restricted-use guidelines, all sample sizes are rounded to the nearest 10.

Dependent variable: Course grades	(1)	(2)	(3)	(4)
Treated × Post × Female	0.547**	0.581**	0.536**	0.570**
	(0.228)	(0.229)	(0.230)	(0.230)
Treated × Post × Job dummy	0.186	0.181		
	(0.156)	(0.148)		
Treated × Post × Job hours			0.072	0.069
			(0.078)	(0.074)
Treated × Post	-0.434**	-0.463**	-0.469**	-0.493**
	(0.218)	(0.219)	(0.219)	(0.220)
Other interaction and standalone indicators	Yes	Yes	Yes	Yes
Student controls	Yes	Yes	Yes	Yes
Geo. demo. Controls	No	Yes	No	Yes
Field of study FE	Yes	Yes	Yes	Yes
Course-semester × Fam. state FE	Yes	Yes	Yes	Yes
Observations	16,770	16,770	16,770	16,770
R-squared	0.525	0.528	0.526	0.529

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).
NOTE: Estimates are weighted based on survey weights for panel analysis.

Table 10. Students' mental health changes.

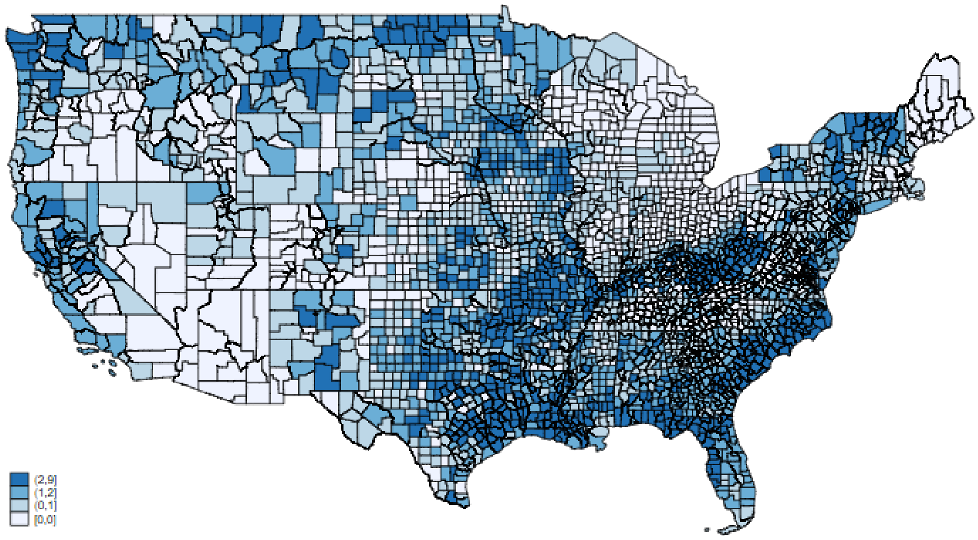
This table reports regression analyses on the effect of family financial shock on students' mental health changes. The dependent variable is the change in students' mental health status surrounding family shocks, based on the five categories of mental status classified by the BPS survey. A lower value indicates greater deterioration in a student's mental health. The sample is based on financially dependent students with available college transcripts information from the BPS12 database. For each treated student A who experiences a family financial shock when enrolled in course X during a semester between academic years 2012 and 2018, we assign control students who are contemporaneously enrolled in the same course X at the same university but do not experience family shocks at that time. Then we examine the mental status changes of these treated-control students. Robust standard errors (Taylor-series linearization) clustered at student origin county and student level are in parentheses. ***, **, and * indicate coefficients significantly different from 0 at the 1%, 5%, and 10% levels, respectively. Per IES restricted-use guidelines, all sample sizes are rounded to the nearest 10.

Dependent variable: Mental status change

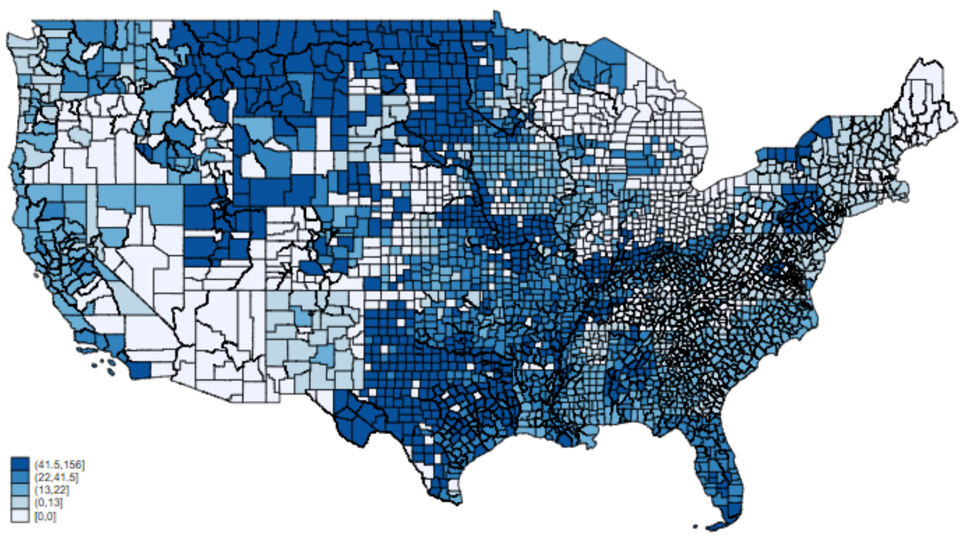
	(1)	(2)	(3)	(4)
Treated × Female			-0.016	0.020
			(0.266)	(0.280)
Treated	-0.520***	-0.521***	-0.511***	-0.532***
	(0.136)	(0.139)	(0.190)	(0.200)
Student controls	Yes	Yes	Yes	Yes
Geo. demo. Controls	No	Yes	No	Yes
Field of study FE	Yes	Yes	Yes	Yes
Course-semester × Fam. state FE	Yes	Yes	Yes	Yes
Observations	670	670	670	670
R-squared	0.649	0.650	0.649	0.650

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).
NOTE: Estimates are weighted based on survey weights for panel analysis.

Online Appendix Tables & Figures



Panel A: Total number of disasters



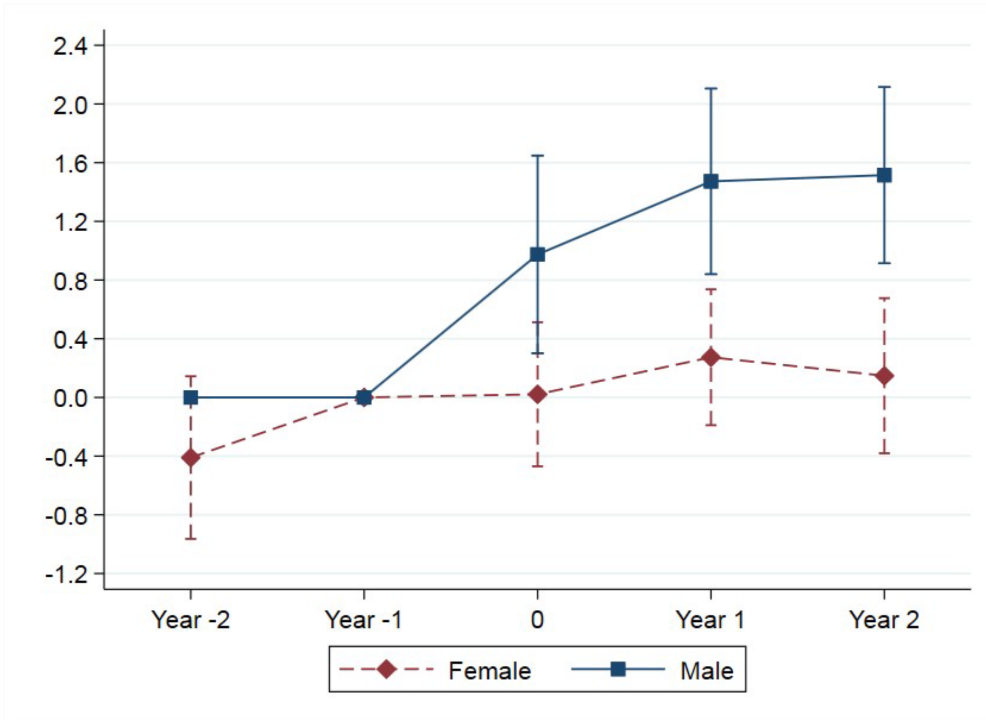
Panel B: Average duration (in days) of disasters

SOURCE: U.S. Federal Emergency Management Agency (FEMA).

Fig. A1. Distribution of natural disasters by counties.

This figure displays the distribution of major natural disasters across U.S. counties between 2011 and 2018. Natural disasters are obtained from the Major Disaster Declarations of the Federal Emergency Management Agency. Panel A displays the total number of disasters experienced by each county. Panel B displays the average duration of disasters (in number of days) each county experiences. The legend denotes the magnitudes of disasters, in terms of the total number (Panel A) and average duration (Panel B); darker counties exhibit greater magnitudes than lighter counties.

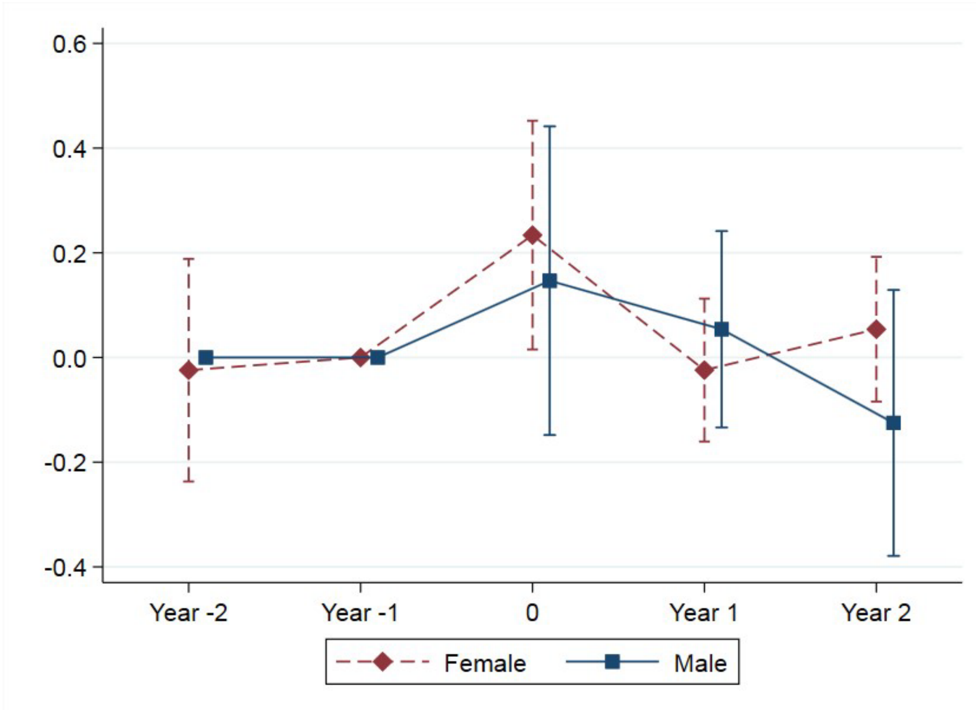
Part-time job hours (log)



SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).
NOTE: Estimates are weighted based on survey weights for panel analysis.

Fig. A2. Dynamics of part-time job take-up over event time among female and male students.

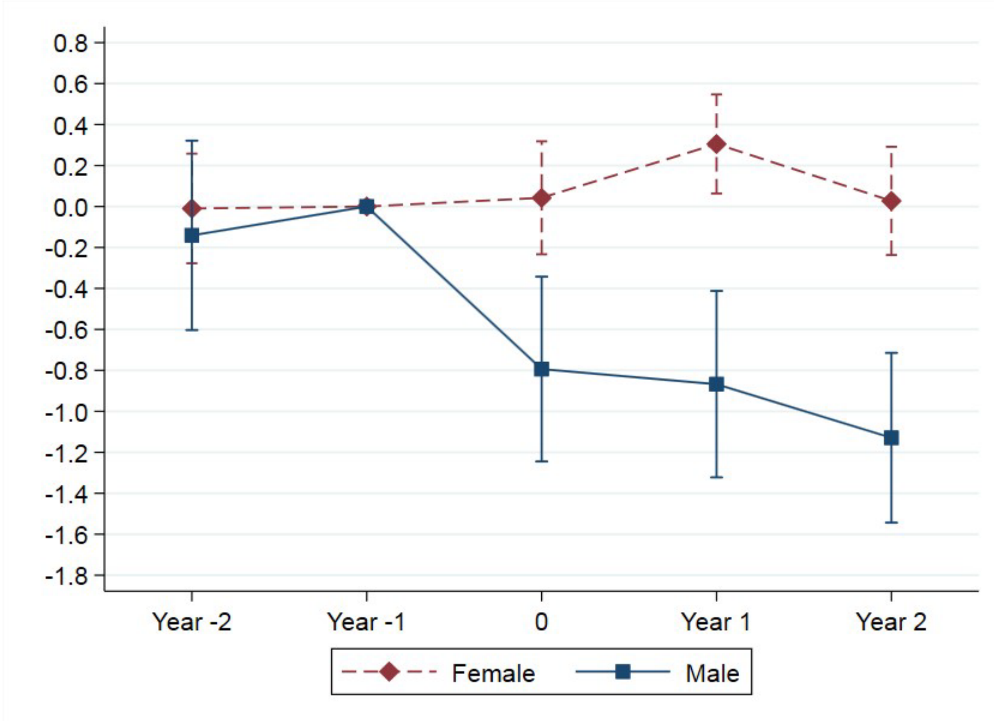
This figure plots the coefficients of the interaction between *Treated* and event time to analyze students' part-time job take-up over event time relative to the control students, separately for female (the dashed line) and male students (the solid line). Time 0 denotes the academic year end when a student experiences the family financial shock. To plot the dashed line, for each female treated student A who experiences a family shock when enrolled in course X during a semester, we assign female control students who are contemporaneously enrolled in the same course X at the same university but do not experience the shocks at that time. Then we track the part-time job take-up of these female treated and control students over time from two academic years before the year of shock to two years after. Part-time job take-up is captured by the logarithm of one plus the number of weekly employment hours at part-time jobs. Part-time jobs require fewer than 40 hours per week on average in an academic year. The year prior to the year of shock (i.e., Year -1) is omitted as the baseline. To plot the solid line, we perform the same analyses among male students. The dashed line presents a difference-in-difference estimation among female students, and the solid line presents a difference-in-difference estimation among male students. The contrast between the two lines presents a triple-difference estimation. The estimation at Year -2 for male students is missing (and therefore assigned to zero) due to insufficient number of observations. The bars surrounding each coefficient represent the two-sided 90% confidence intervals.



SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).
NOTE: Estimates are weighted based on survey weights for panel analysis.

Fig. A3. Dynamics of student debt borrowing over event time among female and male students.

This figure plots the coefficients of the interaction between *Treated* and event time to analyze students' federal student loan borrowing over event time relative to the control students, separately for female (the dashed line) and male students (the solid line). Time 0 denotes the academic year end when a student experiences the family financial shock. To plot the dashed line, for each female treated student A who experiences a family shock when enrolled in course X during a semester, we assign female control students who are contemporaneously enrolled in the same course X at the same university but do not experience the shocks at that time. Then we track the student debt borrowing of these female treated and control students over time from two academic years before the year of shock to two years after. Student debt borrowing is captured by the logarithm of one plus the total amount of federal student loans. The year prior to the year of shock (i.e., Year -1) is omitted as the baseline. To plot the solid line, we perform the same analyses among male students. The dashed line presents a difference-in-difference estimation among female students, and the solid line presents a difference-in-difference estimation among male students. The contrast between the two lines presents a triple-difference estimation. The estimation at Year -2 for male students is missing (and therefore assigned to zero) due to insufficient number of observations. The bars surrounding each coefficient represent the two-sided 90% confidence intervals.



SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).
NOTE: Estimates are weighted based on survey weights for panel analysis.

Fig. A4. Sun and Abraham (2021) estimator.

This figure performs similar analyses as in Figure 2 using the Sun and Abraham (2021) estimator. The control students consist of those whose families never experience natural disasters over the sample period, and the figure plots the coefficients of the interaction between *Treated* and event time obtained from the Sun and Abraham (2021) interaction-weighted (IW) estimators, in which each cohort is defined at the semi-academic year level. The dashed line pertains to female students, and the solid line pertains to male students. The bars surrounding each coefficient represent the two-sided 90% confidence intervals.

Table A1. Changes in family financial conditions following natural disasters.

This table reports difference-in-differences analyses of the effect of disasters on students' family financial conditions. The dependent variables are a student parents' taxes paid (proxy for total income), earnings, and savings, respectively, scaled by the 2012 tuition of the student's school. The sample is constructed as in Table 3. $Year_0$ is an indicator that equals one for the year-end when the disaster happens. $Year_{-1}$ ($Year_1$) is an indicator that equals one for the year end before (after) the disaster year. $Year_{-2}$ ($Year_2$) is an indicator that equals one for the second year end before (after). The interaction between *Treated* and $Year_{-1}$ is omitted as the baseline. Controls include *Female*, *White*, *Age*, *Parents' college degree*, *Number in college*, *Non-traditional index*, and student field of studies. Control variables are described in Table 2. Parental savings are winsorized at the 5th and 95th percentiles due to many missing values. Interactions between event time indicators and control variables are included but not reported. Robust standard errors (Taylor-series linearization) clustered at the student origin county and student level are in parentheses. ***, **, and * indicate coefficients significantly different from 0 at the 1%, 5%, and 10% levels, respectively. Per IES restricted-use guidelines, all sample sizes are rounded to the nearest 10.

Dependent variables:	Taxes paid (proxy for total income)	Earnings	Savings
	(1)	(2)	(3)
Treated (0, 1) × $Year_{-2}$	-0.047	-0.859	-0.178
	(0.143)	(0.902)	(0.233)
Treated (0, 1) × $Year_{-1}$	Baseline	Baseline	Baseline
Treated (0, 1) × $Year_0$	-0.224**	-1.412**	-0.576***
	(0.111)	(0.651)	(0.214)
Treated (0, 1) × $Year_1$	-0.201*	-1.026	-0.945***
	(0.119)	(0.718)	(0.320)
Treated (0, 1) × $Year_2$	-0.200	-1.758	-0.651
	(0.246)	(1.395)	(0.773)
Student and family controls	Yes	Yes	Yes
Field of study FE	Yes	Yes	Yes
Course-semester × Fam. state × Event year FE	Yes	Yes	Yes
Observations	5,190	5,220	2,610
R-squared	0.609	0.702	0.610

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).
NOTE: Estimates are weighted based on survey weights for panel analysis.

Table A2. Family financial shocks and academic performance of female and male students – more stringent assignment of controls.

This table repeats the analyses in Table 3 with a more stringent assignment of control students. For each treated student A who experiences a family financial shock when enrolled in course X during a semester between academic years 2012 and 2018, we assign control students B who are enrolled in the same course X at the same university during the same semester but do not experience family shocks at that time. Then we look for courses Y that treated student A and control students B are both enrolled in before and after the semester of shock to compare their grades in each course. The dependent variable is a student's normalized transcript grade for the course. The regression specifications follow those in Table 3. Robust standard errors (Taylor-series linearization) clustered at the student origin county and student level are in parentheses. ***, **, and * indicate coefficients significantly different from 0 at the 1%, 5%, and 10% levels, respectively. Per IES restricted-use guidelines, all sample sizes are rounded to the nearest 10.

Dependent variable: Course grades			
	(1)	(2)	(3)
Treated × Post × Female	0.517*	0.607**	0.734***
	(0.291)	(0.279)	(0.278)
Treated × Post	-0.419*	-0.483**	-0.574**
	(0.235)	(0.244)	(0.239)
Other interaction and standalone indicators	Yes	Yes	Yes
Student controls	No	Yes	Yes
Geo. demo. Controls	No	No	Yes
Field of study FE	No	Yes	Yes
Course-semester × Fam. state × Event time FE	Yes	Yes	Yes
Observations	8,650	7,010	7,010
R-squared	0.508	0.592	0.599

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).
NOTE: Estimates are weighted based on survey weights for panel analysis.