Grit and Credit Risk: Evidence from Student Loans*

Jess Cornaggia[a], Kimberly J. Cornaggia[a,†], Han Xia[b]

[a] Smeal College of Business, Penn State University, University Park, PA 16802
[b] School of Management, SM14.326, University of Texas at Dallas, Richardson, TX 75080

First Draft: October 26, 2018
This Draft: November 16, 2020

Abstract

With a license to use individually identifiable information, including college transcripts, we find that students who quit courses during college are 13% more likely to default on student loans than their perseverant peers, controlling for conventional risk factors. This effect is especially strong when students quit courses in their chosen major and courses at more selective institutions. Similarly, students who voluntarily repeat courses after performing poorly are 13% less likely to default than peers who give up. This effect is stronger when social / monetary costs of repeating courses are especially high. Students' early-life behavior provides an observable credit risk indicator.

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

Keywords: Student loans, Grit, Perseverance, Credit risk factors, Household finance

---

* We are grateful to the Institute of Education Sciences (IES) of the United States Department of Education for access to individually identifiable information on student loan borrowers subject to IES License Control Numbers 18030002 and 18030003. We thank Brent Ambrose, Andra Ghent, Camelia Kuhnen, Brian Melzer, Adair Morse, Michaela Pagel, Kim Peijnenburg, Christophe Spaenjers, Constantine Yannelis, seminar participants at the Norwegian School of Economics, Penn State University, and audience members at the 2019 Carnegie Mellon – Penn State – University of Pittsburgh Conference, 2019 Northern Finance Association, and 2019 Western Finance Association for comments and suggestions, and Simran Dhingra, Brian Gibbons, and Zihan Ye for research assistance.

† Corresponding author. Tel: 814-865-2243; fax: 814-865-3362; E-mail address: kcornaggia@psu.edu.

"You can quit. But you can't quit until the season is over, the tuition payment is up, or some other 'natural' stopping point has arrived. You must, at least for the interval to which you've committed yourself, finish whatever you begin, (pg. 241)"

-- Genius Grant Recipient Angela Duckworth, *Grit: The Power of Passion and Perseverance*

1. Introduction

The purpose of this paper is to expand the literature on student loan default to examine the role of students' early-life behavior. Specifically, we test whether quitting or persevering in the face of challenges during college predicts future student loan default, controlling for cognitive and financial ability to repay loans. Prior literature establishes a link between credit risk and various demographic characteristics and self-reported unobservable psychological traits. We are first to establish this link between credit risk and individuals' *observable behavior*. Further, we are first to introduce the concept of "grit" to the financial economics literature.[1]

Quitting behavior is antithetical to the concept of personal grit, the commitment to finish what one starts, even when challenges emerge. We hypothesize that such commitment is particularly important for long-term goals, such as debt repayment. In long-term endeavors, circumstances often deviate from expectations and adjusting to the unexpected is potentially costly (e.g., individuals must work longer hours to fulfill debt obligations). While committed individuals work to overcome these challenges, less resilient people may not persevere and potentially default. Our focus on observable behavior, rather than borrower psychology, should be of practical use to creditors. According to a recent article in the *Wall Street Journal*, FinTech lenders search for observable indicators of borrower grit in order to identify loan candidates among applicants with low FICO scores.[2] Our study directly contributes to this effort.

To identify quitting behavior, we obtain a license to use individually identifiable information from the U.S. Department of Education. The data contain comprehensive transcript

[1] See Duckworth, Peterson, Matthews, and Kelly (2007) for an introduction to this field and see Section 2.2.3 for a review of related literature.

[2] See "Need Cash? Companies are Considering Magazine Subscriptions and Phone Bills when Making Loans" by Amanda Andriotis, September 12, 2019.

information for a representative sample of students, including registered courses, enrollment semesters (terms), reported grades, and course actions such as late-semester withdrawal and course repetition. This information enables us to identify students' quitting behavior in two ways.

Our first way identifies quitting behavior as late-semester course withdrawal. Students commit to a class after a trial period (they do not drop the course during the allotted drop/add period). Later, when the course or other aspects of life progress unexpectedly, some students quit the course. We compare default outcomes of quitting students with outcomes of control students who are enrolled in the *same* courses at the *same* academic institutions, have similarly committed to the courses after a trial period, but do not later withdraw from any courses. By fixing students within the same courses, this identification strategy ensures that differences in students' behavior do not simply reflect heterogeneous challenges posed by class characteristics.

Our second way relates to voluntary course repetition following poor performance (e.g. grades C- or D). Poor academic performance provides a well-defined adverse situation. Facing this challenge, students choose either to retake the course to better master the material or to give up. We compare default outcomes of students who repeat courses after earning a low grade with outcomes of other students enrolled in the same courses at the same academic institutions, who have similarly earned a low grade, but forgo the opportunity to retake the course. Because treatment and control students perform equally poorly in the same classes, this identification strategy further mutes heterogeneity in students' endowed *abilities* and helps isolate students' *commitment* to overcome challenges.

We posit that students' commitment to overcome challenges in their education is analogous to their commitment to repay student loans. We thus hypothesize that (1) students quitting courses late in the term exhibit higher default rates than peers who persevere, and (2) students voluntarily repeating courses default less frequently than students who give up after equally poor performance. By combining this observed behavior with data containing students' complete federal loan receipt and repayment histories, we are able to empirically test our hypotheses.

In the baseline analyses, we find a strong relation between students' early quitting behavior (for college courses) and future quitting behavior (for student loan defaults). Because this correlation is robust to controls for students' achievement during college (GPA, major, and degree attainment), financial position after college (income, borrowed amount, mortgages and other debt, and family obligations), and demographic characteristics (age, ethnicity, and gender), it suggests that student commitment is a credit risk factor distinct from conventional observable determinants. This interpretation, however, may be confounded by unobservable factors. For example, students may quit due to debilitating accidents or deaths of family members. These personal circumstances may keep students from completing (or repeating) courses, and subsequently impact their financial ability to repay loans after college, despite of their willingness to work through the challenges. Such omitted factors can therefore drive both students' early quitting behavior and future default.

To address this concern, we take advantage of another feature in our data and create a parsimonious control for potential unobservable factors. For each student loan, we observe whether a student applies for and receives a repayment deferment (which allows a borrower to temporarily stop making payments), the reasons for the deferment, and the granted duration of the deferment. We identify deferment due to "unemployment" or "economic hardship" and include fixed effects for the duration of such deferment in the estimation. Because deferment duration is determined by the severity of economic hardship or the period of unemployment verifiable by the loan servicer, these fixed effects essentially capture the magnitude of students' economic challenges to repay loans, and thus any unobservable factors (such as personal circumstances) that have led to these economic challenges.

Controlling for both observable characteristics and proxies for potential unobservable confounding factors, we observe that students who withdraw from college courses late in the term are 13% more likely to default on student loans than their peers who do not quit. Likewise, students who repeat courses following poor performance are 13% less likely to default than their peers who quit after equally poor performance in the same courses at the same institutions. We conclude that student commitment (grit) is a significant credit risk factor, distinct from demographics or unobservable characteristics leading to economic challenges, as well as cognitive and financial abilities to repay loans. In fact, one contribution we make to prior literature is evidence that after controlling for individual grit, gender and ethnicity no longer correlate with student loan default.

Our identification of quitting behavior based on course repetition following poor performance helps mute heterogeneity in students' intellectual abilities in driving default outcomes. We provide cross-sectional tests to further disentangle student commitment from ability, as well as unobservable personal circumstances. Intuitively, if quitting courses indicates a lack of grit, then such indication should be stronger when quitting comes at a high cost. We thus expect to observe a stronger relation between course withdrawal and default when the opportunities for gains from education are greater (and hence, when quitting is more costly). This is indeed what we find. We show that withdrawal has a stronger predictive power for default when students withdraw from courses in more-selective schools than in schools with higher acceptance rates, when students quit a course in their chosen major compared to withdrawn courses outside their major, and when students quit courses in more lucrative disciplines, such as engineering or computer science, compared to arts or humanities. These results lend further support to the role of students' commitment to overcome challenges in predicting future default. These cross-sectional results cannot be explained alternatively by the observed quitting behavior simply reflecting variation in students' abilities or unobservable personal circumstances.[3]

Similarly, if the behavior of repeating courses following poor performance indicates student grit, then such indication should be stronger when repeating comes at a higher cost. We therefore separate students based on the social and monetary cost of repeating courses. We show that repeating courses predicts lower default especially when students face a long commute to universities, when they have children and/or full-time employment during college, and among

[3] Our attempt to distinguish a student's commitment to repay her loans from her ability to do so is similar in nature to the attempt of Berg, Burg, Gombovic, and Puri (2019) to disentangle the extent to which digital footprints proxy for financial characteristics versus those traditionally viewed as soft information.

students enrolled in colleges with high tuition. These results again suggest that student commitment to overcome challenges plays a distinct role in predicting future default risk.

We provide additional tests to address potential alternative explanations for our results. In particular, we are concerned about strategic default (e.g., Yannelis, 2016). For example, students may (1) strategically withdraw from courses in order to manage their transcripts and (2) delay payments on subsidized student loans in order to first pay down other debt accruing at higher interest rates. We address this concern by identifying, and excluding from analyses, withdrawal and default decisions that are plausibly strategic. Our results are robust to this exclusion.

We also consider the extent to which the quitting behavior we observe reflects certain psychological traits (self-efficacy, instability, and patience) previously shown to be correlated with credit risk. Our rich dataset allows us to create proxies for these traits in a manner similar to prior research and our results are robust to their inclusion. Final robustness tests include the use of continuous outcome variables – outstanding loan amounts at default (as a percentage of amount borrowed) – rather than a default indicator, examination of Stafford loans only, and incorporating course failures into our measure of quitting. Our results are robust and our conclusions are unchanged.

Our results are relevant to the debate over student-level underwriting in taxpayer-subsidized lending.[4] For third-party lenders and governments that already employ student-level underwriting, our results commend the inclusion of risk factors capturing borrowers' commitment to managing repayment as well as financial ability to do so.[5] Indeed, prior evidence from the U.S. mortgage market indicates the value of qualitative risk assessment. According to Moody's (2015), when borrowers are under stress, Residential Mortgage Backed Securities (RMBS) backed by loans for which qualitative underwriting factors are strong outperform those backed by loans for which qualitative factors are weak, even if the quantitative factors are similar.

[4] Student loan underwriting in the U.S. is performed at the level of academic institution; for details, see Darolia (2013).
[5] For example, Brazil recently incorporated student-level underwriting; for details see Reuters (2017).

Our results further suggest potential policy prescriptions for the academic institutions eligible for federal financial aid (or on the cusp of eligibility). To the extent that grit can be fostered (e.g., Alan, Boneva, and Ertac; 2019), our results commend such efforts by colleges and universities with high student default rates.[6] Efforts on the part of academic institutions to reduce student loan default are especially prudent as policymakers consider holding these institutions accountable for their defaulting students' obligations; see Bayer, Hastings, Neilson, and Zimmerman (2015), Looney and Watson (2018) and the proposed Promoting Real Opportunity, Success, and Prosperity through Education Reform (PROSPER) Act.

2. Institutional detail and literature review

2.1. Institutional detail

At the close of 2019, outstanding student loan balances in the U.S. totaled $1.51 trillion (FRB of New York, 2019) with the greatest growth rate among low-income zip codes (Amromin and McGranahan, 2015). The student loan delinquency rate roughly doubled since the pre-crisis era with the sharpest increase over the 2012-2013 period. Although current default rates are below historic peaks (e.g., 1991), credible forecasters predict that nearly 40% of student borrowers will default over the 20-year horizon following their college entrance; Scott-Clayton (2018).

The public student loan program in the U.S. is largely risk-insensitive and taxpayers bear the cost of inefficient allocation of capital. Underwriting guidelines are imposed only coarsely and at the institution-level: institutions with the highest default rates (40% in one year or 30% annualized over three years) are subsequently ineligible for federal loans. Otherwise, interest rates are set by federal law and are a function of loan type and disbursement date. Rates are thus equivalent within a cohort regardless of whether borrowers finance a four-year degree from an AACSB-accredited institution or a two-year degree from an online for-profit program.[7] Although

[6] In Norway, for example, students are rewarded financially for completing courses and attaining degrees; https://www.lanekassen.no/nb-NO/Stipend-og-lan/Hoyere-utdanning/Omgjoring-av-lan-til-stipend/.
For anecdotal evidence, please see: https://mobile.twitter.com/ValaAfshar/status/1112438818978840580

[7] Congressionally-mandated interest rates do not exactly imply that students have no economic incentive to maintain

private sector loans have higher interest and default rates (e.g., Eaton, Howell, and Yannelis, 2018), analyses from Sun and Yannelis (2016) and Cox (2017) indicate welfare gains from access to private lending. Our study contributes to the effort to identify observable credit risk indicators in the private loan market.

Important for our empirical design, certain students are eligible for loan deferment which allows a borrower to temporarily stop making payments. Because borrowers with deferred subsidized loans are not responsible for interest accrual during the deferment period, loan deferment is a valuable alternative to loan forbearance and the income-based repayment programs available for those with low-paying jobs.[8] Loan deferment is granted for various reasons and can be renewed up to three years. Of particular interest for our study are deferments for "unemployment" and "economic hardship." Such deferment is granted after a borrower's unemployment or economic hardship status is verified by the loan servicer, and it ends when a borrower is no longer eligible (e.g., when an unemployed student successfully lands a job). Our data allow us to observe the start and end dates of each student loan deferment, which we utilize to control for the magnitude of borrowers' economic challenges.

2.2. Related literature

2.2.1. Costs and benefits of (public) debt-financed education

In theory, government subsidies in student borrowing relax tight credit that would otherwise result from moral hazard and adverse selection; e.g., Stiglitz and Weiss, (1981) and Mankiw (1986). The potential benefit of expanding subsidized credit is the investment in human capital among marginal borrowers. The potential costs of this credit expansion are higher tuition rates (Lucca, Nadauld, and Shen, 2019) and higher student loan default rates (e.g., Looney and Yannelis, 2018). Policymakers thus face a tradeoff between improved access to education and

their credit scores. In addition to other risk-sensitive debt, such as auto loans and residential mortgages, students with high FICO scores can later refinance their student loans at better terms than their peers with lower FICO scores.

[8] For details on eligibility and terms of loan forbearance and deferment, see the U.S. Department of Education's Office of Federal Student Aid: https://studentaid.ed.gov/sa/repay-loans/deferment-forbearance. Regarding income-based repayment programs, see https://studentaid.ed.gov/sa/repay-loans/understand/plans/income-driven.

expected costs to taxpayers (e.g., Amromin and Eberly, 2016) especially if college education is not a wise choice for all (e.g., Carneiro, Heckman, and Vytlacil, 2011; Heckman, Humphries, and Veramendi, 2018).[9]

Several papers focus on other (non-default) consequences of increased student debt including delayed family formation (Gicheva, 2011), reduction in small business formation (Ambrose, Cordell, and Ma, 2015), reduction in graduate school enrollment (Fos, Liberman, and Yannelis, 2017), hindered entrepreneurship (Krishnan and Wang, 2018), reduction in home ownership (Cooper and Wang, 2014; Mezza, Ringo, Sherlund, and Sommer, 2016), reduction in stock market participation (Batkeyev, Krishnan, and Nandy, 2017), and suboptimal labor market outcomes (Minicozzi, 2005; Rothstein and Rouse, 2011; Luo and Mongey, 2017; Ji, 2018; Weidner, 2018). These consequences notwithstanding, Avery and Turner (2012) argue that students should collectively borrow more, not less, as the benefits to education outweigh the economic costs, with the possible exception of for-profit colleges.

2.2.2. Student loan default

Early research on demographic factors associated with default (ethnicity, gender, age, and family income) examines high default rates in a period where student debt was dischargable in bankruptcy.[10] More recent studies find that these demographic factors remain significantly correlated with student loan debt levels and repayment difficulty in a more stringent legal environment (e.g., Choy and Li, 2006; Lochner and Monge-Naranjo, 2014; Shapiro, 2014; Fox et al. 2017). We therefore incorporate demographic factors into our empirical models.

[9] Garratt and Marshall (1994) model direct taxpayer funding of college education (distinct from indirect taxpayer subsidization of student loans). Also related are studies of economic impacts of earlier (childhood) education subsidies; e.g., Lee and Seshardi (2019) and Caucutt and Lochner (2020).

[10] Early studies documenting higher default rates among minority students include the U.S. Department of Education (1978), Wilms et al. (1987), Knapp and Seaks (1992), Flint (1994, 1995), and Volkwein and Szelest (1995). Volkwein et al. (1995) confirm the correlation between ethnicity and default but find that marriage status and number of children are more important predictors. Knapp and Seaks (1992) and Wilms et al. (1987) further find that default is inversely related to family income and Knapp and Seaks (1992) report that default risk is increasing in student age.

Other recent papers examine default rates by institution type and find that for-profit schools and online programs exhibit higher default rates than traditional in-residence programs at public or non-profit private schools (e.g. Looney and Yannelis, 2015, 2018; Armona, Chakrabarti, and Lovenheim (2017). Cellini and Turner (2018) find little or no earnings gain from attending for-profit colleges, comparing graduates to comparable high school graduates with no college education. Eaton, Howell, and Yannelis (2018) extend this line of inquiry to examine returns to private equity investment in for-profit academic institutions. Their results suggest that private equity buyouts lead to higher enrollment and higher profits, but lower education inputs, higher per-student debt levels, lower graduation rates and earnings, and therefore lower student loan repayment rates. Based on these findings, we account for institution type in our analysis.

Finally, Mueller and Yannelis (2018) find that student loan default risk is influenced by declining real estate values, particularly among college graduates earning less than $60,000. In our student loan default analysis, we control for graduates' income and mortgage debt.

2.2.3. Effects of grit and non-cognitive traits

Duckworth et al. (2007) develop a self-reported questionnaire called the Grit Scale. These authors measure the relation of grit to successful outcomes including educational attainment among adults, GPA among Ivy League undergraduates, dropout rates among USMA and West Point cadets, and ranking in the National Spelling Bee. Duckworth and Quinn (2009) improve on the original Grit Scale with a shortened "Grit-S" scale. Follow-up papers contrast the concept of grit from related personal attributes (Duckworth and Gross, 2014) and test the impact of grit on success in various venues (Duckworth et al. 2009, and Duckworth et al. 2011). Eskreis-Winkler et al. (2014) report that gritty individuals finish high school and college, are more likely to stay married, more likely to keep their jobs, and less likely to drop out of the military.[11] The quitting behavior we observe is antithetical to individual grit.

[11] Crede et al. (2017) provide a critical review of this literature, noting that self-reported grit could reflect the same traits as previous psychological constructs. Our focus on observable behavior, rather than unobservable psychological traits, circumvents the need for such distinction.

Although we are first to connect grit to financial economics literature, prior papers examine effects of other non-cognitive traits on economic outcomes. For example, Heckman et al. (2006) employ the National Longitudinal Survey of Youth (NLSY), which includes scores for cognitive skills from the Armed Services Vocational Aptitude Battery (ASVAB) and measures of non-cognitive traits from the Rotter Locus of Control Scale and Rosenberg Self-Esteem Scale. Using a matching model to mitigate endogeneity issues, the authors find that non-cognitive skills raise wages through direct effects on productivity and indirect effects on schooling and experience.[12]

Puri and Robinson (2007) rely on survey data obtained from the Survey of Consumer Finance to develop a novel measure of optimism. These authors link individual optimism to numerous work/life choices including whether to marry, when to retire, whether to invest in individual stocks, and how much to save. However, these authors do not use their measure of individual optimism to predict loan defaults.

Kuhnen and Melzer (K&M, 2017) employ NLSY survey data to investigate the impact of self-efficacy on financial distress. The authors define self-efficacy as the strength of individuals' beliefs that their personal effort influences future outcomes and find that people with higher self-efficacy are less likely to experience financial distress. Parise and Peijnenburg (P&P, 2019) employ survey data from the Longitudinal Internet Studies for Social Sciences (LISS) to investigate the impact of emotional stability and conscientiousness on financial distress. These authors find that individuals in the bottom quintiles for both of these noncognitive traits are 10 times as likely to experience financial distress than those in the top quintiles for both traits.

Our study complements these prior studies in several ways. First, we are concerned with observable behavior rather than underlying psychological traits. Our simple research question is whether quitting college courses predicts student loan default, controlling for cognitive and financial ability to repay loans. Our approach allows us to parsimoniously link individuals' early-

[12] Also relevant is the literature review provided by Heckman, Humphries, and Mader (2011) who summarize that the General Educational Development (GED) credential fails to capture relevant non-cognitive skills such as persistence, motivation, and reliability required to obtain college degrees and favorable labor market outcomes.

life quitting behavior (based on college course withdrawal or course repetitions) to later-life quitting behavior (loan default), without appealing to specific underlying psychological characteristics unobservable to lenders.

Second, K&M (2017) and P&P (2019) indicate that potential channels through which noncognitive traits affect financial distress include inadequate savings, proneness to income shocks and susceptibility to unemployment. These circumstances diminish individuals' ability to repay debt. In our analyses, we include fixed effects for the duration of loan deferment (which reflects the magnitude of post-college economic challenges), and therefore control for students' financial inability to repay loans. We show that after controlling for financial inability to pay, students' early-life commitment to overcome challenges continues to predict future loan default. This finding highlights the distinction between individuals' *ability* to pay and their *willingness* to honor the repayment commitment when circumstances unfold unexpectedly.[13]

Third, we extend the analysis in K&M (2017) and P&P (2019) of credit cards, vehicle loans, and residential mortgages to federal student loans, which differ in important ways. Most notably, federal student loans are (1) taxpayer subsidized, (2) indefinitely non-dischargeable in bankruptcy court, and (3) predicted by many to soon face crisis. Understanding students' default decisions on their subsidized loans is relevant to the current debate over the tradeoff between improved access to education and costs to taxpayers.

Fourth and finally, recent papers provide empirical evidence that, unlike psychological characteristics, grit can be taught and learned. Alan et al. (2019) capitalize on a randomized educational intervention implemented in Istanbul to show that grit can be fostered in a classroom environment; treated students score 0.28 standard deviations higher on a standardized math test compared to control students. Using results from the same experiment, Alan and Ertac (2019) find evidence that coaching grit in the classroom closes the gender gap in student competitiveness.

[13] Indeed, supplementary tests confirm that quitting behavior predicts student loan default after controlling for psychological traits (self-efficacy, instability, and patience) previously shown to be correlated with credit risk.

Although they do not attribute their results to individual grit, evidence from Heller, et al. (2017) demonstrates that interventions in the lives of disadvantaged youth influence decision making, increase graduation rates, and reduce crime. Collectively, the evidence in these papers support our conclusions and policy recommendations for academic institutions to encourage student perseverance and reduce defaults by their students.

3. Data and sample construction

3.1. Sample construction

The National Center for Education Statistics (NCES) is the part of the U.S. Department of Education's Institute of Education Sciences (IES) that collects, analyzes, and publishes statistics on education and school information. In particular, the NCES conducts the Beginning Postsecondary Students Longitudinal Study (BPS), which we utilize for our study. The BPS surveys a representative sample of students who began their postsecondary education for the first time during different academic years at eligible postsecondary institutions in the United States or Puerto Rico. The sampling of the BPS is conducted at two stages. The BPS first selects a sample of representative postsecondary institutions, and then among these institutions, a sample of representative eligible students. The institutions eligible for the BPS sample are required to meet all criteria for distributing federal aid authorized under Title IV of the Higher Education Act (20 U.S.C. 1070-1099). Institutions providing only vocational, recreational, remedial courses, only in-house courses for their own employees, or U.S. service academies are excluded. The students eligible for the BPS sample are those who are enrolled in (1) an academic program, (2) at least one course for credit that could be applied toward fulfilling the requirements for an academic degree, or (3) an occupational or vocational program that required at least 3 months or 300 clock hours of instruction to receive a degree, certificate, or other formal award. Students who are concurrently enrolled in high school or in a General Educational Development (GED) program or other high school completion program are excluded.

The BPS is conducted every eight years and the most recent three surveys consist of student cohorts entering college in 1996, 2004, and 2012. For each cohort, the BPS interviews students at three points in time: at the end of their first year of enrollment, and then three and six years thereafter. The BPS collects data on a variety of topics, including student demographic characteristics, school and work experiences, transfer, and degree attainment. We obtain a license from the NCES to access information from all three BPS cohorts in 1996, 2004, and 2012.

The 2004 cohort (hereafter, BPS04) offers a unique feature necessary for our study: complete transcript information. This information enables us to identify coursework, grades, and most importantly, course-related actions including late semester withdrawal (i.e., withdrawal from courses late enough in the term to record a grade "W" on the transcript) and repeating courses after poor performance. We supplement BPS04 with the 2015 Federal Student Aid (FSA) administrative data obtained from the National Student Loan Data System (NSLDS), which provide complete federal loan receipt and repayment histories up to June 2015, and the use of repayment options such as deferment, consolidation, and default for each surveyed student in BPS04.[14] The intersection of the FSA and transcript information enables us to examine the effect of students' course withdrawal and course repeats on loan default. This intersection results in our universal sample of 15,730 students with required college transcripts and student loan information.

3.2. Descriptive statistics

Table 1 describes this universal sample, with summary statistics on key characteristics of course withdrawal, repeat, loan information, deferment of repayment, and default. The IES requires us to coarsen reported sample sizes to assure the anonymity of individuals in the sample. Per these restricted-use guidelines, we round all sample sizes to the nearest 10. We winsorize continuous variables at the 1% and 99% percentile level. Just over half (8,100) of our sample

[14] Our repayment period follows key changes in federal law regarding lender recourse. Wage garnishment of delinquent borrowers began in 1991 and in 1998 federal student loans became indefinitely non-dischargeable in bankruptcy. However, wage garnishment to repay student loans is secondary to child support and IRS levies and limited to a portion of disposable income; garnishment is capped at 15% for student loans and 25% across obligations.

students withdraw from at least one course late enough in the term to earn a grade “W”. Of these students, the average withdraws from 3.169 courses; this distribution is positively skewed with a median of two courses and some students withdrawing from four or more courses. Of the 15,730 students,19.5% repeat at least one college course (with a mean of 2.85 courses). On average, students who repeat courses do so following a grade of D+, with the top 25th percentile of students repeating following a grade of C- or higher, and the bottom 25th percentile of students repeating following a grade of D or lower.

[Insert Table 1 near here.]

Of the 15,730 students, 64.6% have student loans. The average of these students borrows $41,070. The standard deviation in loan amount reflects the skewness in this distribution; some borrow over $400,000. Of the 10,170 borrowers, 21.6% apply for and obtain payment deferment due to unemployment or economic hardship. These students have higher levels of debt ($51,237 on average) than the average borrower. Of the 2,200 students who obtain deferment, the average deferment period (without required payments) is 410 days. The average deferring student obtains deferment 603 days after making his first payment.

Of the 10,170 students with loans, 26.5% default. Default is defined by the U.S. Department of Education as non-payment for 270 days.[15] Of the 2,200 students who obtain deferment, the default rate rises to 34.8%. We further observe that defaulting students have less student loan debt ($30,757, on average) compared to the sample average borrower ($41,070). The average defaulting student defaults 931 days after making his first payment, with a loan amount of $13,052. At the 75th percentile, default occurs 1,280 days out.

Figures 1 displays above- and below-median default rates by state of default borrowers’ universities. We observe no pattern suggesting that regional cultural or economic conditions drive student loan default.

[Insert Figure 1 near here.]

[15] We exclude loans whose repayments are interrupted due to e.g., loan cancellation and repurchase by universities.

3.3. Correlation

In Table 2, we present Pearson correlation coefficients among scholastic, financial, and demographic characteristics shown previously correlated with student loan default. Column (1) displays correlations with the indicator *Default* and is of most interest. Because all coefficients in this column are highly significant, we suppress for space asterisks indicating statistical significance in this table. As expected, *Default* is significantly negatively related to overall college GPA (a proxy for cognitive ability) and the income students earn in 2009 (the last round of survey for the 2004 cohort). Because our sample of students enters college in 2004, income in 2009 likely reflects income from students' first jobs after graduation. *Default* is likewise negatively related to degree attainment, parental income, and parental assistance, as expected.[16] Regarding demographics, *Default* is positively related to student age; less likely among female students; more likely among black students; more likely among only children in college and students with children of their own during school. Working during school is negatively correlated with *Default*, suggesting that work ethic may offset effects of disadvantageous financial situation. Regarding institutional characteristics, *Default* is more likely among for-profit institutions offering certificates or 2-year degrees (relative to public or non-profit schools offering 4-year degrees). The negative correlation between *Default* and loan amount category is also established in prior literature. Although credit risk increases in leverage ceteris paribus, lower loan amounts are also correlated with less selective institutions and failure to matriculate. This result highlights the need to control for institution, matriculation, and other covariates in formal tests of our hypotheses.

[Insert Table 2 near here.]

4. Empirical Results

[16] Parental income affects the quality of preparation provided by public elementary and secondary schools in the U.S. (e.g. Hoxby, 1998) and college attendance (e.g. Lochner and Monge-Naranjo, 2011; Solis, 2017). Cameron and Heckman (2001) suggest that long-run factors associated with background and family environment matter more than simple funding constraints. Similarly, Kane (1994) attributes increases in college enrollment among black students in the 1980s to increases in these students' parental education. Plug and Vijverberg (2003) suggest these parental affects are approximately 55-60% genetically transmitted with 40-45% due to environment.

4.1 Late-semester course withdrawal and student loan default

In this section, we test our hypotheses and examine whether students' early quitting behavior (for college courses) predicts late quitting behavior (for student loans). We first identify students' quitting behavior with late-semester course withdrawal. Treated students commit to a class at the beginning (they do not drop the course during the allotted drop/add period) but withdraw late in the term (*Withdrawal*=1); control students enroll in these same (withdrawn) courses at the same universities, similarly commit to these courses after the trial period, but never quit any college course (*Withdrawal*=0). We hypothesize that students quitting courses exhibit higher default rates than control students who persevere.

In Figure 2, we plot the cumulative default probabilities over time relative to students' first loan repayment, separately for these two groups of students. The x-axis denotes the number of years since the first loan repayment (i.e., year "0"). The y-axis denotes the default probabilities. Consistent with our hypothesis, the cumulative default probability is higher among students who quit college courses at each point in event time.

[Insert Figure 2 near here.]

Panel A of Table 3 tabulates univariate tests between treated and control students, as well as summary statistics for key variables. Unconditionally, students who quit courses are 14.4% more likely to default on their loans. However, these groups differ significantly along other dimensions shown previously correlated with default. For example, females are less likely than males to quit college courses; black students are more likely than others. Students who quit courses are younger, earn lower grades, and are less likely to attain degrees. After college, they earn less income, and are more likely to apply for and receive loan deferment. Conditional on deferment being granted, students quitting courses also experience longer deferment duration. In ~~part of~~ our later analyses, we use deferment duration to capture the severity of students' economic hardship verified by the loan servicer.

[Insert Table 3 near here.]

To control for the differences between the two groups of students observed in Panel A, we perform OLS regression analyses and report the results in Panel B of Table 3. Column (1) reports the most parsimonious specification, employing the unconditional sample of students:

$$Default_{i,k} = \alpha_k + \beta \times Withdrawal_{i,k} + Other\ FE + \ Controls + \varepsilon, \quad (1)$$

where i indicates a student and k indicates a course. $Withdrawal$ is the key variable of interest, which indicates whether student *i* withdraws from course *k* or not. The dependent variable *Default* is an indicator for whether a student i attending course k has defaulted on any of his loans as of June 2015. Following Kuhnen and Melzer (2017), we estimate Equation (1) using linear probability models. Linear probability models usually generate more precise estimates of marginal effects (Angrist and Pischke, 2008) and more importantly, they allow us to include high-dimensional fixed effects.[17]

α_k denotes course fixed effects. Including course fixed effects allows us to mute exogenous heterogeneity in class characteristics, such as difficulty of course content, that may influence withdrawal decisions differently between treatment and control students. Because we examine late-term withdrawal, course fixed effects also control for students' heterogeneous assessments of the course ex ante (i.e., during the add/drop period) due to heterogeneity in ambition or optimism.

We cluster standard errors at the student and institution level. In Column (1), we observe that students who quit college courses are 15.3% more likely to default on their loans than their peers enrolled in the same courses at the same institutions. In Column (2), we include additional observable characteristics that capture students' intellectual abilities, scholastic abilities and financial abilities. They include student age when enrolled in college, degree attainment, GPA, field of study, as well as fixed effects for post college income categories, and loan amount categories. Fixed effects for income (and loan amount) categories are indicators for each tercile of the distribution of students' income in 2009 (and loan amount borrowed). We use categorical rather

[17] A Probit model with a large number of fixed effects typically generate biased estimators (Greene, 2004).

than continuous measures for these variables to account for their potential nonlinear effect on default.[18] These controls address concerns that students quitting college courses may be less likely to attain a degree, may have selected into a more challenging major field of study, may have lower cognitive abilities (resulting in different GPA within a given field of study), and/or may have borrowed more to attend the same institutions due to disadvantageous financial circumstances – any one of which may lead to poorer financial standing and subsequently higher default rates.

Column (3) further controls for student gender and ethnicity. In both Columns (2) and (3), the magnitude of the coefficient on the key variable *Withdrawal* is reduced, though it remains statistically significant. Taken together, these observations suggest that students' early quitting behavior is a credit risk indicator distinct from demographic factors and cognitive and financial ability to repay debt.

In our analyses, we exclude students who withdraw from *all courses* in any given term, as they likely face personal or family tragedy. To further address concern over confounding unobservable circumstances (e.g., debilitating accidents), we take advantage of another feature of our data.

In addition to default outcomes, for each loan we observe whether a borrower applies for and receives loan deferment, the reasons for loan deferment, and the granted deferment duration. Because the duration of such deferment is determined by the severity of the hardship verifiable by the loan servicer, its duration captures the magnitude of the economic challenge. We therefore condition our sample to include only those students who obtain deferment due to "unemployment" or "economic hardship" and include fixed effects for deferment duration. These fixed effects provide a parsimonious control for students' economic challenges, and thus any unobservable

[18] For example, an increase in annual income from $1,000 to $1,500 is unlikely to affect default outcomes (i.e., default is likely to happen in both cases). An increase from $100,000 to $150,000 is likewise unlikely to affect default (i.e., default is likely to happen in neither case). However, changing from one income category to another category is more likely to influence default. Changes in loan amounts are similarly non-linear in relation to student loan default.

factors (such as personal circumstances) that have led to these challenges.[19] Specifically, we estimate OLS regressions as in Equation (2).

$$Default_{i,k} = \alpha_k + \beta \times Withdrawal_{i,k} + Deferment\ duration\ FE + Other\ FE + \\ + Controls + \varepsilon. \quad (2)$$

Results are tabulated in Columns (4) – (9) of Table 3 Panel B.

Column (4) replicates Column (1) but for the constrained (conditioned) sample of students who obtain loan deferment. Column (5) adds the deferment duration fixed effects, which are indicators for monthly intervals of deferment duration granted due to unemployment or economic hardship (i.e., less than one month, between one month and two months,…, between 35 months and 36 months, and more than 36 months). Both columns suggest that students who quit college courses are approximately 13% more likely to default on their loans than their peers enrolled in the same courses at the same institutions. Columns (6) and (7) add the control variables from Columns (2) and (3), respectively, and indicate that students who quit college courses are 9.5% - 12.8% more likely to default than their peers enrolled in the same courses at the same institutions, controlling for student demographics, degree attainment, chosen major field of study, GPA, loan amount, and post-college incomes. In Column (8), we control for students' mortgage and other outstanding debt (e.g. credit cards), which potentially affect student loan default risk through total student leverage.

In Column (9), we take one further step to examine whether quitting behavior simply reflects students' academic abilities. Here we take advantage of detailed class enrollment information and calculate students' performance in common non-withdrawn classes. Specifically, for a treatment student *A* withdrawing from class *X* and a control student *B* completing class *X*, we identify classes *Y* that are in the same field as class *X* and that both students *A* and *B* successfully complete. These common non-withdrawn classes provide an opportunity to observe students'

[19] Alternatively, we can keep the unconditioned sample and let deferment duration equal zero if students do not apply for deferment. This approach generates qualitatively similar results. We apply the conditioned sample here to better assure that default outcomes are not driven by whether students face post-college economic challenge to start with.

ability to handle academic challenges absent withdrawals. We control for treatment and control students' GPA of the common classes in lieu of overall college GPA. By definition, this control reduces our sample size to observations with available common classes. We find consistent results in Column (9).

Overall, by controlling for both observable characteristics and proxies for unobservable confounding factors, we conclude from Panel B of Table 3 that the effect of early-life quitting behavior on future student loan default is not explained by the rigor of the curriculum, students' cognitive abilities, a mechanical link between poor academic performance and future financial standing, or economically-important circumstances. We therefore conclude that students' early quitting behavior is a distinct credit risk factor. An additional noteworthy result from Table 3 Panel B is the diminished significance of student gender and ethnicity in relation to student loan default, after controlling for students' quitting behavior.

4.2. Cross-sectional analysis based on late-semester course withdrawal

Next, we provide cross-sectional tests to further disentangle student commitment from ability and unobservable personal circumstances. We posit that when quitting comes at a high cost, the behavior of quitting serves as a stronger indication for lack of grit. We therefore predict that high-cost quitting should have greater effects on future loan default. To test this prediction, we perform cross-sectional analyses based on the relative costs of quitting. First, because failure in foundational material is of greater consequence than failure in marginally relevant material, we examine the effects of withdrawing from courses in the students' chosen majors compared to the effects of withdrawing from courses outside the major. We expect that quitting courses related to one's chosen major is a stronger predictor of future default than quitting courses that are marginally related. Second, because the financial costs (tuition) of education are higher and the expected earnings benefits are greater at more exclusive/selective institutions (e.g., Chetty et al., 2020), we compare the effects of withdrawing from courses at more-selective institutions to the effects of withdrawing from courses at more-inclusive schools. We expect that quitting at a selective institution is a stronger predictor of future default than quitting at more inclusive schools.[20] Third, because the financial rewards (expected future income) for success are higher from STEM courses than for courses in the arts, social sciences, and humanities, we compare the effects of withdrawing from major courses in lucrative fields of study compared to those with lower future earnings prospects.[21] We expect that quitting lucrative classes is a stronger predictor of future default than quitting less-lucrative classes.

This is indeed what we find. Specifically, we replicate the results from Column (6) in Table 3 Panel B, but separately consider withdrawing from major and non-major courses, from courses at more- and less-selective schools, and from more- and less-lucrative fields of study.[22] We tabulate these results in Table 4. Controlling for student age, degree attainment, and fixed effects for specific courses at specific institutions, deferment duration, income categories, GPA categories, field of study, and loan amount categories, we observe that students who quit major courses are 38.2% more likely to default than their perseverant peers; this difference is significant at 5% (Column (1) of Table 4). The difference between students quitting non-major electives and their control peers is not significant (Column (2) of Table 4). The second difference in the effect of quitting on default rates between students quitting major versus non-major courses is significant at 5% (as shown at the bottom of Table 4).

[Insert Table 4 near here.]

With the same set of controls, in Columns (3) and (4), we show that students who quit courses at relatively selective institutions are 23.4% more likely to default than their perseverant

[20] We identify academic institutions' exclusivity based on universities' self-reported admissions rates. We classify the bottom quartile of institutions (those with the lowest in-sample acceptance rates) as "more-selective" and the other 75% of the sample (those with higher acceptance rates) as "less-selective" institutions. Dale and Krueger (2002) demonstrate the endogeneity of elite schools admitting students likely to be higher earners and find that effects of institution selectivity on future earnings are limited to low-income students. We thus additionally motivate our test based on the market value (price of tuition) of the education: we expect stronger effects among students quitting more-valuable courses than students quitting less-valuable courses.

[21] Indeed, Schmeiser, Stoddard, and Urban (2016) find that students who receive information suggesting they may be unlikely to be able to repay their loans are more likely to switch to higher earning majors.

[22] We select Column (6) because additional controls in Column (7) are insignificant in Table 3 and additional controls in Columns (8) and (9) reduce sample size prohibitively for use in cross-sectional analyses.

peers; this difference is significant at 1%. The difference in default rates between quitting and persevering students enrolled in more inclusive schools is not statistically significant. The second difference in the effect of grit on default rates between selective and inclusive schools is significant at 5%. Finally, as shown in Columns (5) and (6), students quitting courses identified as promising more lucrative future earnings have a 21.5% higher default rate than their perseverant peers; this difference is significant at 5%. The difference in default rates between students quitting less lucrative courses and their control peers is not significant. The contrast is economically meaningful, although the second difference is statistically insignificant.

Overall, results in Table 4 further support our conclusion that students' commitment to overcome challenges is a significant credit risk factor. These cross-sectional results cannot be explained alternatively by quitting behavior simply reflecting variation in students' abilities or unobservable personal circumstances.

4.3. Course repetition and student loan default

Our second identification of students' quitting behavior is based on course repetition following poor performance. Because repeating a college course requires time, energy, and tuition, poor performance provides students with an obvious opportunity to quit. We thus predict that students who repeat courses following poor performance are less likely to later default on their student loans, compared to their peers who quit after exhibiting equally poor performance.

To test this prediction, we first define poor academic performance as grades of C- or below, (i.e., from the following set of grades [C-, D+, D, D-]). Grades of C- or below represent the lower tail of a typical grade distribution and are most likely to prompt students to repeat courses (see Table 1). We do not include the fail grade (F) here, because repeating failed courses may be more compulsory. We similarly exclude courses in students' chosen major, because repeating a major course following poor performance may likewise be more compulsory. Lastly, we exclude course repeat followed by withdrawal. We then compare students who repeat courses after earning a low grade with control students who are enrolled in the same courses at the same academic institutions, have similarly earned a low grade, but choose instead to quit (and do not repeat any other college courses). We estimate OLS regressions as in Equation (3):

$$Default_{i,k} = \alpha_k + \beta \times Repeat_{i,k} + Deferment\ duration\ FE + Other\ FE + Controls + \varepsilon, \quad (3)$$

where i indicates a student and k indicates a course. *Default* is an indicator for whether a student i attending course k defaults on any of his loans. *Repeat* is the key variable of interest, which indicates whether student i repeats course k or not, after earning a poor grade. α_k indicates course fixed effects. As in Equation (2), fixed effects for deferment duration capture the magnitude of economic challenges students face after college, and therefore potential unobservable factors that might have led to these challenges.

We report results from Equation (3) in Table 5. Because the number of treatment students (repeating courses) in Table 5 is smaller than the number of treatment students (withdrawing from courses) in Table 3, the sample size in Table 5 is smaller.[23] The parsimonious specification in Column (1) controls only for *Course FE.* Column (2) adds *Deferment duration FE.* Column (3) adds fixed effects for *Income categories, GPA categories*, *Field of study categories*, along with controls for student age when first enrolled in college and degree attainment. Column (4) adds *Loan amount categories FE*, and Column (5) controls for student gender and ethnicity.

[Insert Table 5 near here.]

Coefficients on *Repeat* suggest that students who repeat college course after poor academic performance are 7.3% to 13.2% less likely to default on their loans. Because the treatment and control students perform equally poorly in the same classes, and because both experience a similar extent of financial hardship later in life (as captured by deferment duration), these results are not likely to reflect variation in students' abilities, institutional retake policies, or unobservable confounding factors that affect future financial success. Overall, our results using course repetition

[23] In order to maintain a sufficient sample size for this analysis, we let deferment duration equal zero when students do not receive loan payment deferments, instead of excluding them from the sample as we do in Table 3.

provide further evidence that perseverant students are significantly less likely to default.

4.4. Cross-sectional analyses based on course repetition

We next perform cross-sectional analyses using course repetition following poor academic performance, in a manner similar to Table 4. In particular, we consider the associated cost of repeating a course. We posit that when course repetition is associated with a higher cost, repeating the course serves as a stronger indication of perseverance. We therefore predict that high-cost perseverance should have greater effects on default risk. Specifically, we consider three dimensions to capture the social and monetary cost of repeating courses, including commuting time to universities, opportunity costs for students with children or full-time employment, and institution tuition.[24]

Table 6 reports results from Equation (3) separately for sub-groups of students. Columns (1) and (2) divide the sample based on students' commute time; long commute is defined as 30 miles or further (approximately 30 minutes' drive on freeways or more), and short commute is less than 30 miles.[25] Here, we see that students who repeat college courses and commute at least 30 miles are 22.4% less likely to subsequently default compared to their peers who quit after equally poor performance. In contrast, the difference between the repeating and quitting students is insignificant when the repeating students face a shorter commute time. The second difference in the effect of repeating between students facing longer versus shorter commute is economically significant, although not statistically significant, likely due to the limited sample size.

Columns (3) and (4) divide the sample based on students' opportunity costs; Column (3) considers repeating students with children or full-time employment and Column (4) considers repeating students without children or full-time employment. Here, we see that if students repeat courses even though they face opportunity costs of their time associated with family or career

[24] See Adda, Dustmann, and Stevens (2017) for in depth analysis of the life cycle career costs associated with children.

[25] Here we only consider students pursuing a bachelor's degree since associate's degrees or college certificates are more likely offered online, making the commuting distance irrelevant. Our results, however, are qualitatively similar without this restriction.

burdens, they are 24.6% less likely to subsequently default on their loans compared to their peers who quit after equally poor performance. However, the difference between the repeating and quitting students is insignificant when repeating student do not have family or career burdens.

[Insert Table 6 near here.]

Finally, Columns (5) and (6) divide the sample based on tuition costs; Column (5) considers students repeating courses at schools with higher-than-median tuition and Column (6) considers students repeating courses at schools with lower-than-median tuition. Tuition proxies for the price tag of repeating a course. We see that students who repeat college courses that have a higher price tag are 23.3% less likely to subsequently default on their loans compared to their peers who quit after equally poor performance. In contrast, the difference between the repeating and quitting students becomes insignificant if repeating is less costly.

Overall, results from Table 6 further supports the conclusion that students' early-life behavior significantly predicts future loan default. Again, because these cross-sectional results cannot be explained alternatively by variation in intellectual ability or personal circumstances affecting financial standing, we conclude that student grit is a distinct credit risk factor.

4.5. Continuous dependent variables

In Table 7, we replace the binary dependent variable employed in Tables 3-6 with alternative continuous dependent variables. In the prior tables, the dependent variable is *Default*, a dummy variable that equals one if a student defaults on education loans, and zero otherwise. In this case, the coefficient on the key variable (i.e. *Withdrawal* or *Repeat*) is the percentage change in default probability comparing quitting and persevering students. In Table 7 Columns (1), (2), (5), and (6), the dependent variable is the logarithm of the outstanding student loan amount at the time of loan default, where the default event is identified as before (failure to make a loan payment for 270 days or longer). In Columns (3), (4), (7), and (8), the dependent variable is the ratio of the outstanding student loan amount at the time of loan default scaled by the total loan amount borrowed.[26] Thus, in Table 7 the coefficient on *Withdrawal* in Columns (1) – (4) and the coefficient on *Repeat* in Columns (5) – (8) indicate differences in the amounts defaulted by quitting and persevering students.

[Insert Table 7 near here.]

In Columns (1) and (2), we observe that students who quit college courses later walk away from 108.4% - 119.3% greater debt obligations than their perseverant peers enrolled in the same courses at the same institutions, who face comparable economic hardship after college (captured by deferment duration). In Columns (5) and (6), we observe that students who repeat college courses after poor performance later walk away from 78.3% - 164% less debt than their control peers who quit after equally poor performance in the same courses and later face comparable economic hardship. These results are consistent with students exhibiting early-life quitting behavior defaulting earlier and students exhibiting early-life perseverance paying down more of their debt before capitulating.

The results in Columns (3), (4), (7) and (8) are consistent with this interpretation. Controlling for original loan balances in Columns (4) and (8), we observe that among defaulting students, gritty students pay down a significantly greater percentage of their obligations before they default compared to their quitting peers who default earlier on greater percentages of indebtedness. In Column (4), the difference between the quitting and persevering groups in average percentage of original loan balances repaid prior to default is 7.5% controlling for other factors and is significant at 5%. In Column (8), this difference is 8.6% and significant at 1%.

4.6. Strategic quitting and default

We consider next the possibility of strategic course withdrawal and strategic student loan default, in the spirit of Yannelis (2016). Students may intentionally withdraw from courses late in the semester and retake them when better prepared to earn a favorable grade. They may also delay

[26] By definition, both measures equal zero if a student does not default on the loans.

payments on their subsidized student loans to first pay down auto loans and credit card balances accruing at higher interest rates. In both cases, students postpone (instead of giving up entirely) the fulfillment of their commitment (to finish a course or repay loans). Such strategic behavior could account for both college course withdrawal and student loan default risk.

We provide additional tests to address this concern by identifying, and excluding from analyses, withdrawal and default decisions that are plausibly strategic. Because the notion of strategic withdrawal is that savvy students who face challenges in the term intentionally withdraw and retake a course, withdrawals that are *not* followed by a retake are more difficult to classify as strategic in this sense. Because the notion of strategic default is that financially savvy students first pay down other debt accruing at higher interest rates and then repay their student loans, defaults that are *not* followed by repaid, consolidated, or otherwise rehabilitated are more difficult to classify as strategic.

Following this intuition, we replicate results from Tables 3 and 5 based on two subsamples. In Columns (1) and (2) of Table 8, we discard from the Table 3 sample (1) course withdrawals followed by retakes and (2) loan defaults that are subsequently repaid, consolidated, or otherwise rehabilitated.[27] We observe that students who quit college courses are 7.3% to 9.1% more likely to default on their loans than their perseverant peers (controlling for variables and fixed effects as in Table 3). In Columns (3) and (4), we discard from the Table 5 sample loan defaults that are subsequently repaid, consolidated, or otherwise rehabilitated. We observe that students who repeat college courses after poor academic performance are 8.8% to 9.8% less likely to default on their loans than their peers who quit the same courses after equally poor performance (controlling for variables and fixed effects in Table 5). These results are statistically and economically significant. Overall, we conclude from Table 8 that the predictive power of quitting behavior vis-a-vis default risk is not likely driven by strategic decision making.

[27] Our cohort of students begin college in 2004 and most begin making student loan payments by 2009. Our repayment data run through June 2015, giving us 6.5 years of repayment history.

[Insert Table 8 near here.]

4.7. Relation between observable behavior and unobservable personal traits

The focus of our study is to test whether observable early-life behavior predicts student loan default. Presumably, observable behavior is a byproduct of a host of unobservable personal values and beliefs, personality characteristics, and psychological traits. Therefore, we investigate the extent to which the observed quitting behavior reflects psychological traits previously shown correlated with financial distress.

We argue in Section 2 that because our research question is whether quitting college courses predicts student loan default, our empirical approach is to parsimoniously link these observable behaviors, without assumptions or hypotheses pertaining to underlying psychological characteristics. In addition, the fixed effects for the duration of student loan deferment (which reflects the magnitude of students' economic hardship after college) absorb unobservable factors, including psychological traits affecting income, savings, and other economic factors contributing to the hardship.

In this section, we provide additional robustness tests and include in our analyses empirical proxies for psychological traits examined previously in the literature. Specifically, we construct empirical proxies for (1) self-efficacy in the spirit of Kuhnen and Melzer (2017), (2) emotional instability in the spirit of Gill and Prowse (2016) and Parise and Peijnenburg (2019), and (3) patience in the spirit of DellaVigna and Paserman (2005), Meier and Sprenger (2015), Cadena and Keys (2015), and Alan and Ertac (2018), and add these controls to Equation (2). Because these empirical proxies considerably reduce our sample size, we only utilize late-semester course withdrawal to identify students' quitting behavior. Our purpose is to test whether the effects of early-life quitting behavior on future default risk are robust to the inclusion of these new controls for underlying psychological traits.

In Kuhnen and Melzer (2017), self-efficacy refers to the belief that effort affects outcomes. The BPS04 survey contains students' responses to survey questions including whether a student is interested in political activism, community leadership, or becoming a recognized expert in her field, interests that reveal a student's positive belief that she can affect outcomes through effort. Other questions reveal pre-enrollment self-efficacy regarding degree attainment (i.e., whether the student expects to attain associates, bachelors, masters, or doctorate degrees). We follow Kuhnen and Melzer (2017) to define *Self-efficacy* as the first principle component of indicators of students' responses to these questions. As expected, we observe in Columns (1) and (4) of Table 9 that students with high levels of *Self-efficacy* are less likely to default on their student loans. More importantly, the magnitude on *Withdrawal* is robust to the inclusion of *Self-efficacy*.

[Insert Table 9 near here.]

As in Parise and Peijnenburg (2019), individuals are more likely to be emotionally unstable if they experience family trauma or lack of family support. Based on this intuition, we construct *Instability* as the first principle component of the indicators for student responses to questions on whether her parents are divorced, whether either parent is deceased, whether she obtains financial support from parents, and whether she is from a family whose parental annual income is below $30,000 (identified by BPS04 as a low-income family). As expected, in Columns (2) and (5) of Table 9, we observe that students marked by higher levels of instability are more likely to default on student loans. Again, the magnitude of *Withdrawal* remains significant.

Cadena and Keys (2015) show that impatient individuals are more likely to drop out of college immaturely and Meier and Sprenger (2015) document that impatience is associated with lower creditworthiness. In the spirit of these studies, we construct proxies for patience following DellaVigna and Paserman (2005), based on available BPS04 survey information. In Columns (3) and (6), *Patience* is constructed based on students' survey responses to questions of whether a student has a savings account in 2004, whether a student has a savings account in 2006, and whether a student has taken college level courses during high school. *Patience* is the first principal component of indicators of students' responses to these questions. A higher value indicates more patience. As expected, in Columns (3) and (6) of Table 9, we observe that students with higher levels of patience are less likely to default on student loans. The magnitude of *Withdrawal* remains significant. Overall, results from Table 9 suggest that observable behavior (quitting college courses) is a distinct credit risk factor even controlling for underlying psychological traits.

4.8. Other robustness tests

Because recipients of Perkins loans are generally in greater financial need than recipients of Stafford loans – and therefore face lower interest rates – we test the effects of students' early-life quitting behavior on future default rates specifically for Stafford loans in Columns (1) - (4) of Table 10.[28] Control variables and fixed effects are the same as those employed in the baseline analysis in Tables 3 and 5. Our key results are robust. Controlling for the battery of fixed effects, we observe in Columns (1) and (2) that students who quit college courses are 11.7% to 15% more likely to default on their Stafford loans than their more perseverant peers. In Columns (3) and (4), students who repeat college courses are 11.1% to 17.6% less likely to default on their Stafford loans than their peers who quit after equally poor performance in the same courses.

[Insert Table 10 near here.]

Finally, in Columns (5) and (6) of Table 10, we replicate results from Table 3 after expanding the definition of quitting behavior from course withdrawal to the union of course withdrawal and course failure. We do so to address concerns that students may quit courses without formally withdrawing. Our baseline results and conclusions are robust to this expanded definition. Students quitting (by withdrawal or by failure) are significantly more likely to default on their student loans than their more perseverant peers.

4.9. Interest rates

Having established observable behavior (quitting college courses) as a significant default indicator, the natural next step is to test whether this risk factor is priced. In other asset classes, we would examine whether the observed behavior leads to higher interest rates for subsequent loans. However, the interest rates on the Stafford and Perkins loans in our sample are not sensitive to *any*

[28] Our sample of loans contains 1,210 Perkins loans and 58,210 Stafford loans.

credit risk factors. Interest rates on Stafford loans are set for a particular vintage by Congressional mandate and are fixed for the life of the loan and constant across borrowers. In our sample of 58,210 Stafford loans, the average (median) interest rate is 5.87% (6.80%). Because Perkins loans are available only to the small subset of students with the greatest financial need, they all face a constant 5% interest rate.[29]

However, for private third-party lenders and governments that already employ student-level underwriting, our results commend the inclusion of risk factors capturing both the ability to repay the loan and the *commitment* to manage repayment. Prior evidence from the U.S. mortgage market indicates that loans for which qualitative underwriting factors are strong outperform those for which qualitative factors are weak, even if the quantitative factors are similar; see Moody's (2015). Like residential mortgages, student loans are household debt subject to qualitative risk factors such as the one we identify in this paper.

5. Conclusion

We ask whether individuals' early-life behavior predicts future default risk, controlling for borrowers' alma mater, specific coursework, college GPA, field of study, degree attainment, demographics, and post-graduation income. Our fixed effects for post-college unemployment and economic hardship effectively control for potential unobservable economically-relevant student characteristics or circumstances.

Like cognitive and financial abilities to repay loans, we find that borrowers' commitment to do so plays a significant role in student loan outcomes. We do not conclude that all students require the strength of character we measure here in order to become productive and successful individuals who repay their loans. Indeed, intellectually talented students may succeed solely on the basis of their intelligence. Rather, we conclude that individual commitment and perseverance makes the difference for marginal students when they face hardship. Overall, our results indicate

[29] Under federal law, the authority for schools to make new Perkins loans ended on September 20, 2017 and final disbursements were permitted through June 30, 2018. Our sample from BPS04 contains 1,210 Perkins loans.

that students identified by transcripts as gritty are 13% less likely to later default than their less resilient peers.

Our results do not speak to the welfare effects of commitment from the student perspective. As a committed athlete risks injury on her path to victory, avoided by competitors who drop out of the competition, so too a stubborn dedication to repay student loans may cost the committed borrower significant consumption utility. Our research question is whether individual grit is a credit risk factor that could potentially be priced by lenders and considered by policymakers. Our empirical evidence indicates that observable behavior is an economically significant indicator of student loan default.

In determining appropriate levels of subsidized student debt, policymakers face a tradeoff between improved access to education and costs to taxpayers. We contribute to this policy debate as follows. Our primary contribution is evidence that student loan default is significantly determined by students' commitment to perform. Our results therefore commend (1) institutional investment in student perseverance, particularly among marginal students, and (2) student-level underwriting guidelines that include proxies for students' commitment to repay loans as well as their cognitive and financial ability to do so.

References

Adda, Jérôme, Christian Dustmann, and Katrien Stevens, 2017. The Career Costs of Children, *Journal of Political Economy* 125(2), 293-337.

Alan, Sule, Teodora Boneva, Seda Ertac. 2019. Ever Failed, Try Again, Succeed Better: Results from a Randomized Educational Intervention on Grit. *Quarterly Journal of Economics* 134 (3), 1121-1162.

Alan, Sule, and Seda Ertac, 2018. Fostering Patience in the Classroom: Results from Randomized Educational Intervention. *Journal of Political Economy* 126(5), 1865-1911.

Alan, Sule and Seda Ertac. 2019. Mitigating the Gender Gap in the Willingness to Complete: Evidence from a Randomized Field Experiment. *Journal of the European Economic Association* 17 (4), 1147-1185.

Ambrose, Brent, Cordell, Larry, and Shuwei, Ma. 2015. The impact of student loan debt on small business formation, *Federal Reserve Bank of Philadelphia* working paper No. 15-26.

Amromin, Gene, and Leslie McGranahan. 2015. The Great Recession and Credit Trends across Income Groups. *American Economic Review: Papers & Proceedings*, 105 (5): 147-53.

Amromin, Gene, and Janice Eberly. 2016. Education financing and student lending. *Annual Review of Financial Economics* 8, 289-315.

Angrist, Joshua D., and Jörn-Steffen Pischke, 2008. Mostly harmless econometrics: An empiricist's companion, Princeton University Press, Princeton, NJ.

Armona, Louis, Rajashri Chakrabarti, and Michael Lovenheim. 2018. How does for-profit college attendance affect student loans, defaults, and earnings? *Federal Reserve Bank of New York*.

Avery, C., and Turner, S. 2012. Student loans: Do college students borrow too much—or not enough? *The Journal of Economic Perspectives*, 26(1), 165-192.

Batkeyev, Birzhan, Krishnan, Karthik, and Nandy, Debarshi K. 2017. Student debt and stock market participation. Northeastern University working paper.

Berg, Tobias, Burg, Valentin, Ana Gombović, Ana, and Puri, Manju. 2019. On the Rise of FinTechs: Credit Scoring Using Digital Footprints. *Review of Financial Studies*, forthcoming.

Beyer, Harold, Hastings, Justine, Neilson, Christopher, and Zimmerman, Seth. 2015. Connecting student loans to labor market outcomes: Policy lessons from Chile. *American Economic Review: Papers & Proceedings,* 105(5), 508–13.

Bleemer, Zachary, Brown, Meta, Donghoon Lee, and van der Klaauw, Wilbert, 2014. Debt, jobs, or housing: What's keeping millennials at home? *Federal Reserve Bank of New York* Staff Report No. 700.

Brown, Meta, Grigsby, John, van der Klaauw, Wilbert, Wen, Jaya, and Zafar, Basit. 2016. Financial education and the debt behavior of the young, *Review of Financial Studies* 29(9), 2490-2522.

Cadena, Brian C. and Benjamin J. Keys. 2015. Human capital and the lifetime costs of impatience. *American Economic Journal: Economic Policy* 7(3), 126-153.

Cameron, Stephen V., and James J. Heckman. 2001. The Dynamics of Educational Attainment for Black, Hispanic, and White Males, *Journal of Political Economy* 109(3), 455-499.

Carneiro, Pedro, Heckman, James J., and Vytlacil, Edward J. 2011. Estimating marginal returns to education, *American Economic Review* 101, 2754–2781.

Caucutt, Elizabeth M. and Lance Lochner. 2020. Early and Late Human Capital Investments, Borrowing Constraints, and the Family, *Journal of Political Economy* 128(3), 1065-1147.

CEA, 2016. Investing in higher education: benefits, challenges, and the state of student debt, *Council of Economic Advisers Report*.

Chetty, Raj, John N Friedman, Emmanuel Saez, Nicholas Turner, and Danny Yagan. 2020. Income Segregation and Intergenerational Mobility Across Colleges in the United States. *The Quarterly Journal of Economics*, forthcoming.

Choy, S. P., and Li, X. 2006. Dealing with debt: 1992-93 bachelor's degree recipients 10 years later (NCES 2006-156). Washington, D.C.: National Center for Education Statistics.

Cox, N. 2017. Pricing, selection, and welfare in the student loan market: Evidence from borrower repayment decisions; UC Berkeley working paper.

Cooper, Daniel, and Wang, J. Christina. 2014. Student loan debt and economic outcomes. Federal Reserve Bank of Boston working paper No. 14-7.

Credé, M., M. C. Tynan, and P. D. Harms. 2017. Much Ado about Grit: A Meta-Analytic Synthesis of the Grit Literature. *Journal of Personality and Social Psychology* 113:1–55.

Dale, Stacy Berg, and Alan B. Krueger. 2002. Estimating the Payoff to Attending a More Selective College: An Application of Selection on Observables and Unobservables. *The Quarterly Journal of Economics* 117(4), 1491–1527.

Darolia, Rajeev. 2013. Integrity versus access? The effect of federal financial aid availability on postsecondary enrollment. *Journal of Public Economics*, 106, 101-114.

DellaVigna, S. and Paserman, M.D. 2005, Job search and impatience, *Journal of Labor Economics* 23(3), 527-588.

Duckworth, A., and J. J. Gross. 2014. Self-Control and Grit: Related but Separable Determinants of Success. *Current Directions in Psychological Science* 23:319–25.

Duckworth, A., T. A. Kirby, E. Tsukayama, H. Berstein, and K. A. Ericsson. 2011. Deliberate Practice Spells Success: Why Grittier Competitors Triumph at the National Spelling Bee. *Social Psychological and Personality Science* 2:174–81.

Duckworth, A. L., C. Peterson, M. D. Matthews, and D. R. Kelly. 2007. Grit: Perseverance and Passion for Long-Term Goals. *Journal of Personality and Social Psychology* 92:1087–1101.

Duckworth, A. L., and P. D. Quinn. 2009. Development and Validation of the Short Grit Scale (Grit-S). *Journal of Personality Assessment* 91:166–74.

Duckworth, A. L., P. D. Quinn, and M. E. P. Seligman. 2009. Positive Predictors of Teacher Effectiveness. *Journal of Positive Psychology* 4:540–47.

Eaton, Charlie, Howell, Sabrina, and Yannelis, Constantine. 2018. When investor incentives and consumer interests diverge: Private equity in higher education. NBER working paper 24976.

Eskreis-Winkler, L, Shulman, E.P., Beal, S.A., and A.L. Duckowrth. 2014. The grit effect: predicting retention in the military, the workplace, school and marriage. Frontiers in Psychology 5(36), 1-12.

Federal Reserve Bank of New York, 2019. Center for Microeconomic Data, Quarterly report on household debt and credit 2019:Q4.

Flint, Thomas A. 1994. The federal student loan default cohort: A case study. *Journal of Student Financial Aid* 24(1). 13-30.

Flint, Thomas A. 1997. Predicting student loan defaults. *Journal of Higher Education* 68(3), 322-354.

Fos, Vyacheslav, Liberman, Andres, and Yannelis, Constantine. 2017. Debt and human capital: Evidence from student loans, Boston College working paper.

Fox, Jonathan J., Bartholomae, Suzanne, Letkiewicz, Jodi, and Montalto, Catherine. 2017 College student debt and anticipated repayment difficulty. Iowa State University working paper.

Garratt, Rod, and John M. Marshall, 1994. Public Finance of Private Goods: The Case of College Education, *Journal of Political Economy* 102(3), 566-582.

Gicheva, D., 2011. Does the student-loan burden weigh into the decision to start a family?, University of North Carolina at Greensboro Working paper.

Gill, David and Victoria Prowse. 2016. Cognitive Ability, Character Skills, and Learning to Play Equilibrium: A Level-k Analysis, *Journal of Political Economy* 124(6), 1619-1676.

Greene, W. 2004. The behavior of the maximum likelihood estimator of limited dependent variable models in the presence of fixed effects. *Econometrics Journal* 7:98-119.

Heckman, J. J., J. Stixrud, and S. Urzua. 2006. The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics* 24:411–82.

Heckman, J. J., J. E. Humphries, and N. S. Mader. 2011. The GED. NBER Working Paper No. 16064.

Heckman, James J., John Eric Humphries, and Gregory Veramendi, 2018. Returns to Education: The Causal Effects of Education on Earnings, Health, and Smoking, *Journal of Political Economy* 126(S1), S197-S246.

Heller, Sara B., Anuj K. Shah, Jonathan Guryan, Jens Ludwig, and Sendhil Mullainathan. 2017. Thinking, Fast and Slow? Some Field Experiments to Reduce Crime and Dropout in Chicago. *The Quarterly Journal of Economics* 132(1), 1–54.

Hoxby, Caroline, 1998. How much does school spending depend on family income? The historical origins of the current school finance dilemma, *American Economic Review: Papers & Proceedings,* 88, 309–314.

Ji, Yan. 2018. Job search under debt: Aggregate implications of student loans, HKUST working paper.

Kane, Thomas J. 1994. College Entry by Blacks since 1970: The Role of College Costs, Family Background, and the Returns to Education, *Journal of Political Economy* 102(5), 878-911.

Kelchin, Robert, and Li, Amy. 2015. Which factors affect student loan repayment and default rates? Seaton Hall University working paper.

Knapp, L.G., and Seaks, T.G., 1992. An analysis of the probability of default on federally guaranteed student loans. *The Review of Economics and Statistics* 404-411.

Krishnan, Karthik, and Pinshuo Wang, 2018. The cost of financing education: Can student debt hinder entrepreneurship? *Management Science,* forthcoming.

Kuhnen, Camelia M., and Melzer, Brian T., Non-cognitive abilities and financial delinquency: The role of self-efficacy in avoiding financial distress. University of North Carolina working paper.

Lee, Sang Yoon (Tim), and Ananth Seshadri, 2019. On the Intergenerational Transmission of Economic Status, *Journal of Political Economy* 127(2), 855-921.

Lochner, L. J., and Monge-Naranjo, A. 2011. The nature of credit constraints and human capital. *The American Economic Review* 101(6), 2487-2529.

Lochner, Lance, and Monge-Naranjo, Alexander. 2014. Default and repayment among baccalaureate degree earners. NBER working paper Working Paper 19882

Lochner, Lance, and Monge-Naranjo, Alexander. 2015. Student loans and repayment: Theory, evidence and policy. NBER working paper Working Paper 20849.

Looney, Adam, and Yannelis Constantine. 2015 A crisis in student loans? How changes in the characteristics of borrowers and in the institutions they attended contributed to rising loan defaults. *Brookings Papers on Economic Activity* (Fall 2015), 1-68.

Looney, Adam, and Yannelis, Constantine, 2018. The consequences of student loan credit expansions: Evidence from three decades of default cycles, University of Chicago working paper.

Looney, Adam, and Tara Watson, 2018. A risk-sharing proposal to hold higher ed institutions accountable to their students, Brookings Institution Report, February 22.

Lou, Mi and Mongey, Simon. 2017. Student debt and job choice: Wages vs. job satisfaction. Emory University working paper.

Lucas, Deborah, and Moore, Damien. 2007. Guaranteed versus direct lending: the case of student loans. In *Measuring and managing federal financial risk*, 163–205. University of Chicago Press.

Lucca, David O., Taylor Nadauld, and Karen Shen. 2018. Credit supply and the rise in college tuition: Evidence from the expansion in federal student aid programs. *Review of Financial Studies* 32(2), 423-466.

Mankiw, N. G. 1986. The allocation of credit and financial collapse. *The Quarterly Journal of Economics* (101), 455–70.

Meier, Stephan, and Charles Sprenger, 2015. Temporal stability of time preferences. *Review of Economics and Statistics* (97), 273–286.

Mezza, Alvaro A., Ringo, Daniel R., Sherlund, Shane M., and Sommer, Kamila. 2016. On the effect of student loans on access to homeownership, *Federal Reserve Board Finance and Economics Discussion Series*.

Minicozzi, Alexandra. 2004. The short term effect of educational debt on job decisions. *Economics of Education Review* 417-430.

Moody's Investors Service, 2015. US RMBS: Qualitative underwriting factors differentiate US prime RMBS. Special Comment, May 19.

Mueller, Holger, and Yannelis, Constantine. 2018. The rise in student loan defaults in the great recession. *Journal of Financial Economics*, forthcoming.

Parise, Gianpaolo, and Kim Peijnenburg. 2019. Noncognitive abilities and financial distress: Evidence from a representative household panel. *Review of Financial Studies*, forthcoming.

Plug, Erik, and Wim Vijverberg, 2003. Schooling, Family Background, and Adoption: Is It Nature or Is It Nurture?, *Journal of Political Economy* 111(3), 611-641.

Puri, Manju, and Robinson, David. 2007. Optimism and economic choice. *Journal of Financial Economics* 86, 71-99.

Reuters, 2017. Brazil to toughen student loan rules as defaults rise; July 5.

Rothstein, Jesse, and Rouse, Cecilia Elena. 2011. Constrained after college: Student loans and early-career occupational choices. *Journal of Public Economics* 95(1), 149–163.

Schmeiser, Maximilian, Christiana Stoddard, and Carly Urban. 2016. Student Loan Information Provision and Academic Choices. *American Economic Review: Papers & Proceedings*, 106 (5): 324-28.

Scott-Clayton, Judith. 2018. The looming student loan default crisis is worse than we thought; Economic Studies at Brookings, Evidence Speaks Reports 2 (34).

Shapiro, Robert J. 2014. The flawed reasoning and evidence for the Department of Education's Gainful Employment Regulation of private, for-profit colleges and universities. University of Georgetown working paper.

Solis, A. 2017. Credit access and college enrollment. *Journal of Political Economy* 125 (2), 562-622.

Stiglitz, Joseph. and A. Weiss. 1981. Credit rationing in markets with imperfect information. *American Economic Review*, 393–410.

Sun, Stephen, and Yannelis, Constantine. 2016. Credit constraints and demand for higher education: Evidence from financial deregulation. *Review of Economics and Statistics* 98(1), 12-24.

U.S. Department of Education. 1978. Predicting default and bankruptcy: Factors affecting the repayment status of student loans. P.J. Kuch, Office of Planning, Budgeting, and Evaluation.

United States Senate. 1991. Abuses in Federal Student Aid Programs. Permanent Subcommittee on Investigations of the Committee on Governmental Affairs.

Volkwein, J. Fredericks, and Bruce P. Szelest. 1995. Individual and campus characteristics associated with student loan default. *Research in Higher Education* 36 (1).

Volkwein, J. Fredericks, Alberto F. Cabrera, Bruce P. Szelest, and Michelle R. Napierski. 1994. Factors associated with student loan default among different racial and ethnic groups. University of Albany working paper.

Weidner, Justin. 2016. Does student debt reduce earnings? Princeton University working paper.

Wilms, W.W, Moore, R.W., and Bolus, R.E. 1987.Whose fault is default? A study of the impact of student characteristics and institutional practices on guaranteed student loan default rates in California. *Educational Evaluation and Policy Analysis 9(1), 41-54.*

Yannelis, Constantine. 2016, Strategic default on student loans, New York University Working Paper.

Table 1. Summary statistics of universal sample.

This table provides summary statistics of key characteristics of student withdrawal, repeats, student loans, deferment, and default. The sample is based on all students with available college transcripts information from the BPS04 database, which consists of representative students who attend college for the first time during the academic year of 2004-2005 in the U.S. *Withdrawal* is a dummy variable that indicates whether a student has ever withdrawn courses during college enrollment. *Number of withdrawals* is the total number of courses from which a student withdraws during college enrollment, conditional on a student has ever withdrawn college courses. *Repeat* is a dummy variable that indicates whether a student has ever repeated courses during college enrollment. *Number of repeats* is the total number of courses a student repeats during college enrollment, conditional on a student has ever repeated college courses, where the repeat information is from the BPS04 database. *Non-fail grades followed by repeats* is the grade above failure that are followed by a course repeat. *Student has a loan* is a dummy variable that indicates whether a student borrowed an education loan during college enrollment. *Total amount borrowed* indicates the original amount of education loans borrowed by a student in nominal U.S. dollars. *Deferment* is a dummy variable that indicates whether a student has been granted loan repayment deferments due to verified unemployment or economic hardships as of June 2015. *Deferment duration* is the number of days granted to a student to defer the payment of his student loans. *Reported number of days since first payment* is the number of days since the student first starts to make a payment of education loans until being granted the repayment deferment (or until default). *Default* is a dummy variable that indicates whether a student has defaulted on the education loans he borrows as of June 2015, where a default is identified if a student fails to make loan payments for 270 days or more as of June 2015. *Total amount borrowed in default* is the amount of loans a student borrows that are in default in nominal U.S. dollars. *Default conditional on deferment* is a dummy variable that indicates if a student has ever defaulted on the education loans he borrows, conditional on the student being granted loan payment deferments as of June 2015. Default information is from the BPS04 database. Per IES restricted-use guidelines, all sample sizes are rounded to the nearest 10.

	N	Mean	Median	S.D.	25th	75th
Withdrawal						
Withdrawal (0,1)	15,730	0.514	1	0.500	0	1
Conditional on withdrawals						
Number of withdrawals	8,100	3.169	2	2.918	1	4
Repeat						
Repeat (0,1)	15,730	0.195	0	0.396	0	0
Conditional on repeats						
Number of repeats	3,070	2.850	2	2.824	1	4
Non-fail grades followed by repeats	2,450	D+	D	-	C-	D
Student loans						
Student has borrowed a loan (0,1)	15,730	0.646	1	0.478	0	1
Conditional on students with a loan						
Total amount borrowed ($)	10,170	41,070	23,495	53,579	9,147	50,246
Deferment due to financial distress						
Deferment (0,1)	10,170	0.216	0	0.412	0	0
Conditional on deferment						
Total amount borrowed ($)	2,200	51,237	33,223	58,795	14,657	63,027
Deferment duration (days)	2,200	410	364	233	253	499
Reported number of days since first payment	1,300	603	502	580	207	888
Defaults						
Default (0,1)	10,170	0.265	0	0.441	0	1
Conditional on defaults						
Total amount borrowed ($)	2,690	30,757	16,625	40,617	6,625	40,304
Total amount borrowed in default ($)	2,690	13,052	7,876	12,796	3,938	17,667
Reported number of days since first payment	1,060	931	793	637	390	1,280
Default conditional on deferment (0,1)	2,210	0.348	0	0.477	0	1

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, Beginning Postsecondary Students Longitudinal Study (BPS) 2004 Cohort.

Table 2. Correlation among variables.

This table shows correlation coefficients among credit risk factors. The sample is based on all students with available college transcript information from the BPS04 database, which consists of representative students who attend college for the first time during the academic year of 2004-2005 in the U.S. *Default* is a dummy variable that indicates whether a student has defaulted on his education loans as of June 2015, where default is identified if a student fails to make loan payments for 270 days or more. *College GPA category* is a discrete variable that corresponds to a student's overall GPA during college enrollment, as provided in the BPS04 database (=1 if the student's GPA>=0 & <1; =2 if GPA>=1 & <2; =3 if GPA>=2 & <3; =4 if GPA>=3 & <=4). *log (Income in 2009)* is (the logarithm of one plus) a student's income as of the BPS04 2009 survey. *log(Age)* is (the logarithm of) the age of a student when enrolled in college. *Female*, *Black*, and *Works during college* are indicator variables. *log(Parents income)* is (the logarithm of one plus) a student's parents total income at the time of college enrollment. *Parental assistance* is a dummy variable that indicates whether a student's parents help cover the student's college expenses. *Only child in college* and *Has children* are indicator variables measured when a student is enrolled in college. *Institution type* is a category variable (=1 if an institution is a 4-year public or non-for profit private institution; =2 if it is a 4 year for profit institution; =3 if it is a 2-year public or non-for profit private institution; =4 if it is a 2-year for profit institution; =5 if it is a less than 2-year public or non-for profit private institution; =6 if it is a less than 2 year for profit institution). *Degree* is a dummy variable that indicates whether a student has obtained a college degree as of the BPS04 2009 survey. *Log(Loan amount)* is (the logarithm of one plus) the loan amounts borrowed by a student.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	A	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*	*K*	*L*	*M*	*M*
A: Default (0,1)	1													
B: College GPA category	-0.312	1												
C: log(Income in 2009)	-0.054	-0.003	1											
D: log(Age)	0.041	-0.022	0.012	1										
E: Female (0,1)	-0.004	0.110	-0.027	-0.059	1									
F: Black (0,1)	0.264	-0.246	-0.069	-0.007	0.031	1								
G: Works during college	-0.001	-0.027	0.028	0.008	0.104	-0.037	1							
H: log(Parents income)	-0.188	0.111	0.043	-0.059	-0.051	-0.234	-0.020	1						
I: Parental assistance (0,1)	-0.090	0.036	0.018	-0.057	-0.037	-0.047	-0.091	0.253	1					
J: Only child in college (0,1)	0.084	-0.069	-0.041	-0.025	0.034	0.051	-0.019	-0.101	-0.019	1				
K: Has children (0,1)	0.148	-0.123	-0.051	0.102	0.097	0.100	-0.011	-0.109	-0.176	0.075	1			
L: Institution type	0.131	-0.179	-0.028	0.073	-0.009	0.037	0.018	-0.094	-0.079	0.059	0.175	1		
M: Degree (0, 1)	-0.303	0.483	0.155	-0.021	0.041	-0.156	-0.019	0.144	0.111	-0.055	-0.144	-0.211	1	
N: log(Loan amount)	-0.034	0.083	-0.089	-0.008	0.037	0.054	-0.021	0.093	0.058	0.019	-0.013	-0.074	0.109	1

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, Beginning Postsecondary Students Longitudinal Study (BPS) 2004 Cohort.

Table 3: Analyses of default and college course withdrawals.

This table presents univariate and multivariate analyses of the effect of college course withdrawals on default. Panel A presents the univariate test as well as descriptive statistics of key variables. The sample consists of BPS04 students who withdraw from college courses late in the term (*Withdrawal*=1) and others enrolled in these same (withdrawn) courses at the same universities but who never withdraw from any college course (*Withdrawal*=0). Students attending classes that enroll only withdrawing students or non-withdrawing students are excluded. *Default* is a dummy variable that indicates whether a student has defaulted on his education loans as of June 2015, where default is identified if a student fails to make loan payments for 270 days or more. *Age* is the age of a student when enrolled in college. *College GPA category* is a discrete variable that corresponds to a student's overall GPA during college enrollment, as provided in the BPS04 database (=1 if the student's GPA>=0 & <1; =2 if GPA>=1 & <2; =3 if GPA>=2 & <3; =4 if GPA>=3 & <=4). *Degree* is a dummy variable that indicates whether a student has obtained a college degree as of the BPS04 2009 survey. *Income in 2009* is a student's income as of the BPS04 2009 survey. *Female*, and *Black* are indicator variables. *Loan amount* is the loan amounts borrowed by a student. *Deferment* is a dummy variable that indicates whether a student has been granted loan repayment deferments due to verified unemployment or economic hardships as of June 2015. *Deferment duration* is the number of days granted to a student to defer the payment of his student loans. The descriptive statistics are reported separately for *Withdrawal*=1 and *Withdrawal*=0. Differences in the means of each variable between the two groups are reported in the last column, along with standard errors testing the statistical significance of these differences. Panel B presents the multivariate analyses. Columns (1) to (3) consists of BPS04 students who withdraw from college courses late in the term (*Withdrawal*=1) and others enrolled in these same (withdrawn) courses at the same universities but who never withdraw from any college course (*Withdrawal*=0). Columns (4) to (6) further require all sample students to receive loan payment deferment due to unemployment or economic hardship as of June 2015. Students attending classes that enroll only withdrawing students or non-withdrawing students are excluded. The dependent variable is *Default*. *log (Mortgage)* is (the logarithm of one plus) the total amount of rent and mortgage payment as of the BPS04 2009 survey. *log (Other debt)* is (the logarithm of one plus) the total amount of car payment and credit cards balances as of the BPS04 2009 survey. *Course FE* are indicators for the courses students take. *Deferment duration FE* are indicators for the durations in months of loan payment deferment granted to students due to unemployment or economic hardship: duration less than one month, between one month and two months,…, between 35 months and 36 months, and more than 36 months. *Income categories FE* are indicators for each of the terciles of the distribution of students income in 2009. *Loan amount categories FE* are indicators for each of the terciles of the distribution of loan amount borrowed by the sample students. *GPA categories FE* are indicators for the categories of a student's overall GPA during college enrollment (=1 if the student's GPA>=0 & <1; =2 if GPA>=1 & <2; =3 if GPA>=2 & <3; =4 if GPA>=3 & <=4). *Field of study FE* are indicators for each field of study classified by the 2-digit Classification of Instructional Programs codes. *Common non-withdrawn GPA categories FE* are indicators for the categories of a student's overall GPA calculated based on treatment and control students' common non-withdrawn classes. Specifically, for a treatment student *A* withdrawing class *X* and a control student *B* completing class *X*, we identify classes that are in the same field as class *X* and that both students *A* and *B* complete. These classes are the common non-withdrawn classes. Standard errors clustered at the student and institution level are in parentheses. All other control variables are defined as in Table 1 and Table 2. ***, **, 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.

Panel A: Univariate test and descriptive statistics based on withdrawals

	Withdrawal = 1			*Withdrawal* = 0			
	N	Mean	Median	N	Mean	Median	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(2) - (5)
Default (0,1)	5,680	0.311	0	11,270	0.168	0	0.144***
							(0.007)
Age	4,810	20.369	19	9,350	20.776	19	-0.407***
							(0.073)
College GPA category	5,570	3.003	3	11,060	3.536	4	-0.532***
							(0.012)
Degree (0,1)	5,500	0.396	0	11,010	0.701	1	-0.305***
							(0.008)
Income in 2009	5,360	13,645	0	10,790	18,057	16,000	-4,412***
							(317.061)
Female (0,1)	4,830	0.559	1	9,410	0.602	1	-0.043***
							(0.009)
Black (0,1)	4,180	0.215	0	8,260	0.133	0	0.082***
							(0.007)
Loan amount	5,680	32,569	17,869	11,270	36,326	18,878	-3,756.82***
							(798.145)
Deferment (0,1)	5,680	0.267	0	11,270	0.195	0	0.072***
							-0.007
Deferment duration	1,520	412.807	364	2,200	380.658	349.375	32.149***
							(6.151)

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, Beginning Postsecondary Students Longitudinal Study (BPS) 2004 Cohort.

Panel B: Regression analysis

	Unconditional			Conditional on deferment					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Withdrawal	0.153***	0.051***	0.045**	0.129***	0.133***	0.095**	0.128**	0.186**	0.323***
	(0.015)	(0.018)	(0.019)	(0.037)	(0.036)	(0.045)	(0.060)	(0.081)	(0.031)
log(Age)		0.147**	0.175**			0.596***	0.711***	0.900***	1.249***
		(0.073)	(0.071)			(0.115)	(0.165)	(0.256)	(0.212)
Degree		-0.128***	-0.149***			-0.090	-0.173***	-0.280***	-0.341***
		(0.026)	(0.027)			(0.059)	(0.066)	(0.101)	(0.102)
Female			-0.002				0.072	0.053	-0.851***
			(0.021)				(0.060)	(0.086)	(0.271)
Black			0.188***				0.038	0.152	-0.011
			(0.036)				(0.088)	(0.147)	(0.050)
log (Mortgage)								-0.026**	0.008
								(0.012)	(0.013)
log (Other debt)								0.009	0.058***
								(0.013)	(0.011)
Course FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deferment duration FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Income categories FE	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes
GPA categories FE	No	Yes	Yes	No	No	Yes	Yes	Yes	No
Field of study FE	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Loan amount categories FE	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Common non-withdrawn GPA categories FE	No	No	No	No	No	No	No	No	Yes
Observations	16,950	11,350	9,910	1,280	1,280	790	690	540	220
R-squared	0.367	0.474	0.511	0.407	0.458	0.698	0.744	0.787	0.854

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, Beginning Postsecondary Students Longitudinal Study (BPS) 2004 Cohort.

Table 4: Cross-sectional analyses based on college course withdrawals.

This table presents cross-sectional regression analyses of the effect of college course withdrawals on default. The sample consists of BPS04 students who withdraw from college courses late in the term and others enrolled in these same (withdrawn) courses at the same universities but who never withdraw from any college course. We further require all sample students to receive loan payment deferment as of June 2015. Students attending classes that enroll only withdrawing students or non-withdrawing students are excluded. The dependent variable is *Default*, a dummy variable that equals one if a student has defaulted on the education loans he borrows as of June 2015, and zero otherwise, where default is identified if a student fails to make loan payments for 270 days or more. In Columns (1) and (2), the sample is partitioned based on whether the withdrawn course is a major course or a non-major course. Column (1) contains the subsample of students who withdraw from major courses and their peers who do not withdraw from college courses, and Column (2) contains the subsample of students who withdraw from non-major courses and their peers who do not withdraw from college courses. A course is identified as a major course if the course field classification is the same as the field classification of the student's chosen major during college. The course and student major field classifications are from the BPS04 database. In Columns (3) and (4), the sample is partitioned based on the admission rate of a university, where admission rate is the ratio of the total number of students admitted to the university scaled by the total number of student applicants in the academic year of 2004-2005. Admission and applicant information is from the National Center for Education Statistics. Column (3) contains the subsample of students who withdrawal from college courses while attending universities in the bottom quartile with respect to selectivity (i.e., lowest admission rates) and their peers who do not withdraw from college courses. Column (4) contains the subsample of students who withdrawal from college courses while attending universities outside this selective quartile and their peers who do not withdraw from college courses. In Columns (5) and (6), the sample is partitioned based on whether a student withdraws from a major course in more- or less-lucrative fields of study. More-lucrative courses include engineering, computer science, statistics, law and business-related courses. Column (5) contains the subsample of students who withdraw from more-lucrative courses in more-lucrative majors and their peers who do not withdraw from college courses, and Column (6) contains the subsample of students who withdraw from courses in less-lucrative majors and their peers who do not withdraw from college courses. All other variables are defined in Table 3. Standard errors clustered at the student and institution 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.

	Major courses	Non-major courses	Selective schools	Non-selective schools	More-lucrative	Less-lucrative
	(1)	(2)	(3)	(4)	(5)	(6)
Withdrawal	0.382**	0.037	0.234***	0.044	0.215**	0.036
	(0.185)	(0.057)	(0.088)	(0.068)	(0.096)	(0.066)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Course FE	Yes	Yes	Yes	Yes	Yes	Yes
Deferment duration FE	Yes	Yes	Yes	Yes	Yes	Yes
Income categories FE	Yes	Yes	Yes	Yes	Yes	Yes
GPA categories FE	Yes	Yes	Yes	Yes	Yes	Yes
Field of study FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan amount categories FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	490	750	540	680	530	700
R-squared	0.806	0.738	0.783	0.772	0.809	0.755
		(1) - (2)		*(3) - (4)*		*(5) - (6)*
p-value of differences		0.050**		0.021**		0.377

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, Beginning Postsecondary Students Longitudinal Study (BPS) 2004 Cohort.

Table 5: Analyses of default and college course repeats.

This table presents analyses of the effect of college course repeats on default. The sample consists of BPS04 students who repeat college courses (*Repeat*=1) that are not major courses and in which they obtain a grade of C- or lower (but do not fail or previously withdraw) and others enrolled in these same (repeated) courses at the same universities, who also obtain a grade of C- or lower (but do not fail or previously withdraw) and who never repeat any college course (*Repeat*=0). Students attending classes that enroll only repeating students or non-repeating students are excluded. The dependent variable is *Default*, which is a dummy variable that indicates whether a student has defaulted on his education loans as of June 2015, where default is identified if a student fails to make loan payments for 270 days or more. All other control variables are defined as in Table 3. Standard errors clustered at the student and institution 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.

	(1)	(2)	(3)	(4)	(5)
Repeat	-0.073*	-0.082**	-0.130***	-0.132***	-0.130**
	(0.040)	(0.041)	(0.050)	(0.049)	(0.054)
log(Age)			-0.545	-0.549	-0.230
			(0.615)	(0.618)	(0.881)
Degree			-0.096	-0.096	-0.175
			(0.082)	(0.082)	(0.110)
Female					0.074
					(0.100)
Black					0.307**
					(0.118)
Course FE	Yes	Yes	Yes	Yes	Yes
Deferment duration FE	No	Yes	Yes	Yes	Yes
Income categories FE	No	No	Yes	Yes	Yes
GPA categories FE	No	No	Yes	Yes	Yes
Field of study FE	No	No	Yes	Yes	Yes
Loan amount categories FE	No	No	No	Yes	Yes
Observations	680	680	490	490	410
R-squared	0.444	0.497	0.693	0.693	0.733

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, Beginning Postsecondary Students Longitudinal Study (BPS) 2004 Cohort.

Table 6: Cross-sectional analyses based on college course repeats.

This table presents cross-sectional regression analyses of the effect of college course repeats on default. The sample consists of BPS04 students who repeat college courses that are not major courses and in which they obtain a grade of C- or lower (but do not fail or previously withdraw) and others enrolled in these same (repeated) courses at the same universities, who also obtain a grade of C- or lower (but do not fail or previously withdraw) and who never repeat any college course. Students attending classes that enroll only repeating students or non-repeating students are excluded. A course is identified as a major course if the course field classification is the same as the field classification of the student's chosen major during college. The course and student major field classifications are from the BPS04 database. The dependent variable is *Default*, which is a dummy variable that indicates whether a student has defaulted on his education loans as of June 2015, where default is identified if a student fails to make loan payments for 270 days or more. In Columns (1) and (2), the sample is partitioned based on the distance of students' commute to universities. Column (1) contains the subsample of repeating students whose commute to universities is longer than 30 miles and their peers who do not repeat college courses, and Column (2) contains the subsample of repeating students whose commute to universities is shorter than 30 miles and their peers who do not withdraw from college courses. In Columns (3) and (4), the sample is partitioned based on student's family or career burden. Column (3) contains the subsample of repeating students who are either parents or have full time jobs and their peers who do not repeat college courses. Column (4) contains the subsample of repeating students who are neither parents or have full time jobs and their peers who do not repeat college courses. In Columns (5) and (6), the sample is partitioned based on the financial cost of repeating college courses. Column (5) contains the subsample of students who repeat courses while attending universities that charge tuitions above the sample media and their peers who do not repeat college courses. Column (6) contains the subsample of students who repeat courses while attending universities that charge tuitions below the sample media and their peers who do not repeat college courses. All other variables are defined in Table 3. Standard errors clustered at the student and institution 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.

	Long commute	Short commute	More family or career burden	Less family and career burden	More expensive	Less expensive
	(1)	(2)	(3)	(4)	(5)	(6)
Repeat	-0.224***	0.029	-0.246**	-0.106	-0.233**	-0.124
	(0.070)	(0.148)	(0.103)	(0.170)	(0.109)	(0.094)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Course FE	Yes	Yes	Yes	Yes	Yes	Yes
Deferment duration FE	Yes	Yes	Yes	Yes	Yes	Yes
Income categories FE	Yes	Yes	Yes	Yes	Yes	Yes
GPA categories FE	Yes	Yes	Yes	Yes	Yes	Yes
Field of study FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan amount categories FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	330	320	320	290	360	350
R-squared	0.770	0.767	0.807	0.797	0.749	0.793
		(1) - (2)		*(3) - (4)*		*(5) - (6)*
p-value of differences		0.290		0.006***		0.271

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, Beginning Postsecondary Students Longitudinal Study (BPS) 2004 Cohort.

Table 7. Alternative continuous measures of default.

This table presents regression analyses of the effect of withdrawals and repeats on default, using alternative continuous measures of default. In Columns (1) to (4), the sample consists of BPS04 students who withdraw from college courses late in the term (*Withdrawal*=1) and others enrolled in these same (withdrawn) courses at the same universities but who never withdraw from any college course (*Withdrawal*=0). Students attending classes that enroll only withdrawing students or non-withdrawing students are excluded. We further require all sample students to receive loan payment deferments as of June 2015. In columns (5) to (8), the sample consists of BPS04 students who repeat college courses (*Repeat*=1) that are not major courses and in which they obtain a grade of C- or lower (but do not fail or previously withdraw) and others enrolled in these same (repeated) courses at the same universities, who also obtain a grade of C- or lower (but do not fail or previously withdraw) and who never repeat any college course (*Repeat*=0). Students attending classes that enroll only repeating students or non-repeating students are excluded. In Columns (1) and (2), and Columns (5) and (6), the dependent variable is the logarithm of the outstanding student loan amount at the time of loan default. In Columns (3) and (4), and Columns (7) and (8), the dependent variable is the ratio of the outstanding student loan amount at the time of loan default scaled by the total loan amount borrowed. Default is identified if a student fails to make loan payments for 270 days or more. All other variables are defined in Table 3. Standard errors clustered at the student and institution 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.

	Withdrawal				Repeat			
	Ln (Outstanding loan amount at default)		Outstanding loan amount at default to total amount borrowed		Ln (Outstanding loan amount at default)		Outstanding loan amount at default to total amount borrowed	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Withdrawal	1.084***	1.193**	0.046**	0.075**				
	(0.349)	(0.506)	(0.019)	(0.030)				
Repeat					-0.783**	-1.640***	-0.037*	-0.086***
					(0.359)	(0.482)	(0.022)	(0.031)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Course FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deferment duration FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income categories FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GPA categories FE	No	Yes	No	Yes	No	Yes	No	Yes
Field of study FE	No	Yes	No	Yes	No	Yes	No	Yes
Loan amount categories FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1,140	700	1,140	700	600	440	600	440
R-squared	0.516	0.794	0.561	0.784	0.545	0.776	0.552	0.779

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, Beginning Postsecondary Students Longitudinal Study (BPS) 2004 Cohort.

Table 8. Strategic default.

This table presents analyses mitigating the possibility of students' strategic behavior. Columns (1) and (2) are based on college course withdrawals. Columns (3) and (4) are based on college course repeats. In Columns (1) and (2), we exclude from the sample of analyses in Table 3 students who withdraw from college courses but repeat the same courses subsequently, as well as students who initially default on student loans but later these loans are paid in full, consolidated, rehabilitated, or discharged. In Columns (3) and (4), we exclude from the sample of analyses in Table 5 students who initially default on student loans but later these loans are paid in full, consolidated, rehabilitated, or discharged. The dependent variable is *Default*, a dummy variable that equals one if a student has defaulted on the education loans he borrows as of June 2015, and zero otherwise, where default is identified if a student fails to make loan payments for 270 days or more. All other variables are defined as in Table 3 and Table 5. Standard errors clustered at the student and institution 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.

	(1)	(2)	(3)	(4)
Withdrawal	0.073***	0.091*		
	(0.028)	(0.054)		
Repeat			-0.088**	-0.098**
			(0.036)	(0.049)
Controls	No	Yes	No	Yes
Course FE	Yes	Yes	Yes	Yes
Deferment duration FE	Yes	Yes	Yes	Yes
Income categories FE	No	Yes	No	Yes
GPA categories FE	No	Yes	No	Yes
Field of study FE	No	Yes	No	Yes
Loan amount categories FE	No	Yes	No	Yes
Observations	1,030	650	570	420
R-squared	0.573	0.773	0.529	0.733

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, Beginning Postsecondary Students Longitudinal Study (BPS) 2004 Cohort.

Table 9. Robustness to controls for self-efficacy, emotional instability and patience.

This table presents analyses controlling for proxies of self-efficacy, emotional instability, and patience, in the spirit of Kuhnen and Melzer (2017), Parise and Peijnenburg (2019), and DellaVigna and Paserman (2005). *Self-efficacy* is constructed based on students' survey responses to questions of whether a student aims to change the political structure, whether a student aims to become a community leader, whether a student aims to become a recognized expert in his field, and what is the highest degree a student expects to obtain before she starts college (associates, bachelors, masters, or doctorate). *Self-efficacy* is the first principal component of the indicators of these responses. A higher value indicates higher self-efficacy. *Instability* is constructed based on students' survey responses to questions of whether a student's parents are divorced, whether either of a student's parents is deceased, whether a student gets financial support from parents, and whether a student is from a poor family whose parental annual income is below $30,000. *Instability* is the first principal component of the indicators of these responses. A higher value indicates more emotionally instability. *Patience* is constructed based on students' survey responses to questions of whether a student has a savings account in 2004, whether a student has a savings account in 2006, and whether a student has taken college level courses during high school. *Patience* is the first principal component of the indicators of these responses. A higher value indicates more patience. The dependent variable is *Default*, a dummy variable that equals one if a student has defaulted on the education loans he borrows as of June 2015, and zero otherwise, where default is identified if a student fails to make loan payments for 270 days or more. All control variables are defined as in Table 3. Standard errors clustered at the student and institution 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.

	(1)	(2)	(3)	(4)	(5)	(6)
Withdrawal				0.122*	0.159***	0.269***
				(0.071)	(0.056)	(0.094)
Self-efficacy	-0.104**			-0.076*		
	(0.043)			(0.045)		
Instability		0.101***			0.101***	
		(0.033)			(0.030)	
Patience			-0.161**			-0.161**
			(0.067)			(0.064)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Course FE	Yes	Yes	Yes	Yes	Yes	Yes
Deferment duration FE	Yes	Yes	Yes	Yes	Yes	Yes
Income categories FE	Yes	Yes	Yes	Yes	Yes	Yes
GPA categories FE	Yes	Yes	Yes	Yes	Yes	Yes
Field of study FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan amount categories FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	440	440	410	440	440	410
R-squared	0.877	0.879	0.905	0.878	0.881	0.908

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, Beginning Postsecondary Students Longitudinal Study (BPS) 2004 Cohort.

Table 10. Additional robustness of main analyses.

This table presents robustness tests of the main analyses. The dependent variable is *Default*, a dummy variable that equals one if a student has defaulted on the education loans he borrows as of June 2015, and zero otherwise, where default is identified if a student fails to make loan payments for 270 days or more. Columns (1) to (4) include Stafford loans only. In Columns (5) and (6), we broaden the definition of *Withdrawal* to include students who fail college courses. The treatment students include those withdrawing from college courses late in the term or failing courses. The control students include those who enrolled in these same courses at the same universities but who never withdraw from or fail any college course. Other variables are defined in Table 3. Standard errors clustered at the student and institution 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.

	Stafford loans		Stafford loans		Withdrawal or fail	
	(1)	(2)	(3)	(4)	(5)	(6)
Withdrawal	0.150***	0.117**				
	(0.039)	(0.057)				
Repeat			-0.111**	-0.176***		
			(0.044)	(0.062)		
Withdrawal or fail					0.123***	0.053***
					(0.026)	(0.019)
Controls	No	Yes	No	Yes	No	Yes
Course FE	Yes	Yes	Yes	Yes	Yes	Yes
Deferment duration FE	Yes	Yes	No	Yes	No	Yes
GPA categories	No	Yes	No	Yes	No	Yes
Field of study	No	Yes	No	Yes	No	Yes
Loan amount categories	No	Yes	No	Yes	No	Yes
Observations	1,070	650	560	390	3,350	2,010
R-squared	0.493	0.767	0.542	0.758	0.523	0.659

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, Beginning Postsecondary Students Longitudinal Study (BPS) 2004 Cohort.

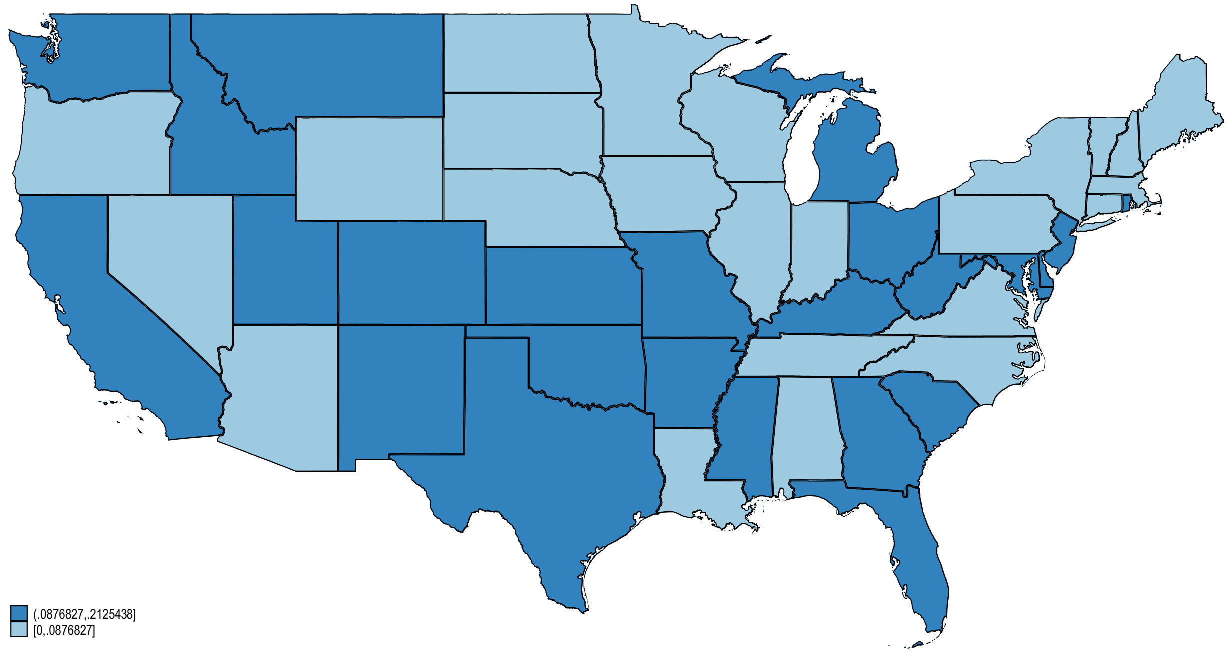

Figure 1. Distribution of defaults by states.

This figure displays whether students enrolled in colleges located in American states default on their student loans at above- or below-median rates. Specifically, this figure presents ratios of defaults. A state's ratio of default is the total number of students in the BPS04 database who default on education loans and are enrolled in colleges located in the state scaled by the total number of students enrolled in colleges in the state. The BPS04 database consists of representative students who begin college during the academic year of 2004-2005 in the U.S. A default is identified if a student fails to make a loan payment for 270 days or more. The legend denotes the magnitudes of the ratio of defaults; darker states exhibit default rates of 8.8% or greater and lighter states exhibit default rates under 8.8%.

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, Beginning Postsecondary Students Longitudinal Study (BPS) 2004 Cohort.

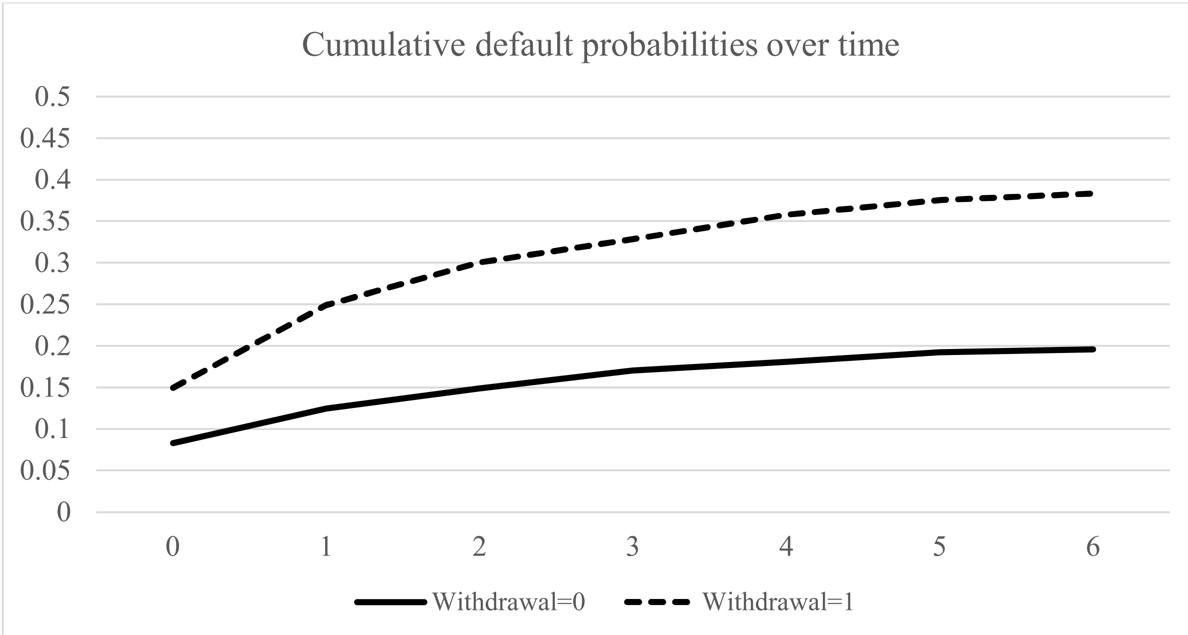

Figure 2. Cumulative default probabilities over time as a function of college course withdrawals.

This figure presents cumulative default probabilities over time relative to the first repayment of student loans. The sample consists of BPS04 students who withdraw from college courses late in the term and others enrolled in these same (withdrawn) courses at the same universities but who never withdraw from any college course. We further require all sample students to receive loan payment deferment due to unemployment or economic hardship as of June 2015. The dotted line represents students who withdraw from at least one college course (*Withdrawal*=1); the solid line represents and those who do not withdraw from any courses during college (*Withdrawal*=0). The x-axis denotes the number of years since the first loan repayment (i.e., year "0"). The y-axis denotes cumulative default probability. A default is identified if a student fails to make a loan payment for 270 days or more.

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, Beginning Postsecondary Students Longitudinal Study (BPS) 2004 Cohort.