Optimism About Graduation and College Financial Aid*

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Abstract

In the United States, college dropout risk is sizable. We provide new empirical evidence that beliefs about the likelihood of earning a bachelor's degree predict college enrollment, and that the distribution of these beliefs exhibits widespread optimism. We incorporate this distribution of beliefs into an overlapping generations model with college as a risky investment that can be financed via federal loans, grants, family transfers, or earnings. We then examine the welfare impact of access to federal student loans. We find that access can reduce welfare for young adults who are low-skilled, poor, and optimistic, due to their mistaken beliefs.

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1 Introduction

In the United States, approximately one third of students who enroll in a bachelor's program fail to complete their degree. These risks may be misunderstood by young people when deciding whether or not to enroll. Access to federal financial aid, in particular student loans, may compound the cosequences of these mistaken beliefs by enabling enrollment driven by optimism with persistent financial consequences; indeed, currently a significant amount of outstanding student debt burdens college dropouts.[1] At the same time, financial constraints may lower the benefits of college for enrollees or prevent some from enrolling who would otherwise benefit from college, rendering the tradeoffs of access to student loans complex.

In this paper, we provide new empirical evidence of widespread optimism about the likelihood of earning a college degree, and build a structural model that embeds these subjective beliefs. We then use the model to analyze the welfare impact of access to federal student loans. In our analysis, welfare is measured using lifetime utilities computed by a planner using the correct probabilities of outcomes, but taking as given consumer choices which are made based on their subjective beliefs. In the context of this paper, "access" refers to the amount that one can borrow from the federal student loan program, as reflected by the borrowing limit (i.e., the intensive margin), rather than access to *any* federal loans (i.e., the extensive margin).

To highlight how access to student loans affects welfare in the presence of widespread optimism, in our main experiment we expand the federal student loan limit. A moderate limit expansion introduces losses to some young adults. Specifically, these losses are experienced by the especially optimistic poor with low skill, whose beliefs lead them to mistakenly transition into college enrollment after the limit expansion but who are more likely to become high-debt dropouts than they anticipate. Large enough limit expansions introduce an offsetting consumption-smoothing benefit, making college enrollment beneficial even for the optimistic poor with low skill. In an additional experiment, we contract the loan limit and find that college enrollees who are optimistic, poor and have low skill in the baseline economy benefit from this policy change because they transition into non-enrollment. This exercise reinforces the results of our main experiment that access to student loans can be harmful to some young adults in the presence of optimistic beliefs.

Our main empirical findings are drawn from two nationally representative panel surveys of young people in the United States: the 1997 National Longitudinal Survey of Youth (NLSY97) and the High School Longitudinal Study of 2009 (HSLS:09). In the NLSY97, we observe expectations about the high school students' probability of earning a 4-year bachelor's degree (BA) by age 30,

[1]Sources: 1997 National Longitudinal Survey of Youth, High School Longitudinal Study of 2009, and authors' calculations.

solicited from both the student and their parent. We show that expected probabilities of earning a BA positively predict college enrollment, controlling for other observable characteristics. We also find that beliefs about one's likelihood of attaining a bachelor's degree among those who later enroll in college far exceed realized college graduation rates: for this group, on average the expected probability of earning a BA by age 30 is 88 percent, yet only 65 percent go on to earn their degree. We conservatively interpret the expected probability of earning a BA as the expected likelihood of graduating college conditional on enrollment.[2] Therefore, the "extent of optimism" among college enrollees, defined as the difference between the average expected BA attainment likelihood and the realized graduation rate, is 23 percentage points; in particular, optimism is highest for enrollees with low skill. Among those who never enroll in college, expectations of the low-skill exhibit sizable optimism when compared to graduation rates of peers with similar skill level who do enroll in a bachelor's degree program. Furthermore, we document similar patterns of subjective beliefs among parents about their child's prospects. We use the HSLS:09 to track a cohort of college enrollees until three years after college enrollment (before repayment begins), and confirm that the amount of federal student debt owed by college dropouts is economically significant at the individual level and in the aggregate.

In light of this evidence, we build a general equilibrium overlapping generations model, where college is a risky investment that can be financed with federal student loans, grants, endogenous family transfers, and labor earnings.[3] Consumers exhibit subjective beliefs about their (or their child's) likelihood of college graduation that may be incorrect, both when they choose whether to enroll in college and when they choose how much wealth to transfer to their child later in life. Furthermore, our model features a production function in which low- and high-education labor are imperfect substitutes. Our model is calibrated to match empirical moments related to the distribution of subjective beliefs, college enrollment and graduation, and family transfers.

Our model performs well in validation exercises related to enrollment responsiveness with respect

[2] For more detail, see the discussion of Table 3 in Section 2.1. Our interpretation is conservative via the following logic. Our main optimism results use expected probabilities reported while the respondent is in high school, which represent the product of the expected likelihood of enrolling in a BA and the expected conditional college graduation likelihood. To identify the conditional expected graduation likelihood, we assume that the expected enrollment probability is 100 percent, implying conditional expected graduation probabilities that are lower bounds. Given true graduation likelihoods, this yields values for the extent of optimism about graduation that are also lower bounds.

[3] This version of our paper abstracts from private students loans. In Moschini, Raveendranathan, and Xu (2023), we show in the data that there is a clear pecking order between federal and private student loans: college enrollees first borrow from the federal student loan program before turning to the private student loan market. Furthermore, private student loans are a small share of total student loans. We view this as evidence that private student loans are a weak substitute for federal student loans. Therefore, the main takeaways of our paper are not sensitive to the omission of private student loans. In fact, in Moschini, Raveendranathan, and Xu (2023) we performed our analysis with private student loans as a weak substitute in our quantitative model, but the main take aways do not change. Here, we abstract from the private student loan market, in order to reduce model complexity.

to both beliefs in the baseline equilibrium's cross-section and to a tuition subsidy in a quasi-natural experiment, as well as in accounting for untargeted skill-specific college wage premiums. We additionally show that, in both the recent U.S. cohort of the HSLS:09 and in the model's baseline equilibrium, many college students fully utilize their federal student loans, which indicates that federal loan limits are binding for college enrollees.[4] These high utilization rates—taken together with our new evidence on widespread optimism among potential college students—motivate our main experiments, in which we examine the impact of access to federal student loans.

In our main model experiment, we expand the federal student loan limit and examine the welfare effects. Beginning with partial equilibrium, we find that the welfare effects of expanding the limit depend on the magnitude of the change: everyone benefits from a large expansion, but a moderate expansion leads to welfare losses for some young adults. These losses are experienced by low-skill young people who are poor and are especially optimistic, and amount to 0.79 percent of lifetime consumption; they do not arise in a re-calibrated model with correct beliefs. In general equilibrium, the limit expansion increases college enrollment and consequently the college education rate in the population, leading to an increase in the wage rate for low-education workers and a decrease in the wage rate for high-education workers. This change in relative prices dampens welfare losses experienced by the optimistic poor with low skill, especially across steady states. However, losses for this group are not entirely eliminated. Furthermore, for those who are high-skill, rich, and optimistic, welfare losses arise due to the decline in wages for workers with a college degree. Similar changes in the wage rates are also observed in the re-calibrated model with correct beliefs, and they have an analogous impact on the welfare of the poor with low skill and the rich with high skill (by construction, beliefs are irrelevant in this framework).

To provide intuition for the source of welfare losses driven by mistaken beliefs, we introduce the concept of being "over-enrolled" in college, which describes a college enrollee who would not have enrolled if their beliefs were correct. We begin by focusing on our limit expansion results in partial equilibrium, where the crucial role of optimistic beliefs is clearest. We prove that, in a simplified partial equilibrium without parental altruism, becoming over-enrolled after a limit expansion is equivalent to experiencing welfare losses. In the partial equilibrium of our quantitative model with altruism, we verify that the close association between becoming over-enrolled and experiencing welfare losses is maintained (although they are not always equivalent). A moderate limit expansion raises over-enrollment; by contrast, a sufficiently large expansion eliminates over-enrollment, because a large increase in access to credit allows an enrollee to better smooth consumption during the college phase to such an extent that the value of college is sufficient to make enrollment beneficial, despite the presence of optimistic beliefs. In general equilibrium, sub-

[4] Sources: HSLS:09, NCES (2019), and a Congressional Research Service report (Smole, 2019), authors' calculations.

jective beliefs continue to have this effect on the enrollment decision, although the welfare cost of over-enrollment is dampened.

We contribute to previous related work that studies college financial aid policies, which includes Caucutt and Kumar (2003), Andolfatto and Gervais (2006), Ionescu (2009), Lochner and Monge-Naranjo (2011), Chatterjee and Ionescu (2012), Krueger and Ludwig (2016), Ionescu and Simpson (2016), Luo and Mongey (2019), Abbott, Gallipoli, Meghir, and Violante (2019), Caucutt and Lochner (2020), and Colas, Findeisen, and Sachs (2021). A key assumption maintained in these studies is that student and parent expectations about academic outcomes are consistent with realized outcomes. In such frameworks, in partial equilibrium without allowing for potential endogenous adjustments to parental transfers, access to federal student loans makes every young adult better off. We incorporate subjective beliefs about the likelihood of college graduation among potential college students and demonstrate that, for some consumers, acces to federal student loans in the presence of optimistic beliefs leads to welfare losses in partial equilibrium. In general equilibrium, these welfare losses are dampened (especially across steady states) but not eliminated.[5]

Our new empirical evidence on the expected likelihood of college graduation complements previous work by Stinebrickner and Stinebrickner (2012). That influential study examines a panel survey of students at a small U.S. college, and finds evidence of optimism about future academic performance. Using this information, the authors then infer the extent of optimism about college graduation among college students in their sample, and find it to be sizable. We use reported expectations about education attainment in the NLSY97, a nationally representative survey, to provide new evidence on the distribution of subjective beliefs in the population of *potential* college students about the likelihood of attaining a bachelor's degree. We show that these beliefs positively predict college enrollment. We also find that there is widespread optimism about one's likelihood of completing a bachelor's degree among college enrollees, especially for those with low skill, and that among those who never enroll in college the low-skill exhibit sizable optimism. Furthermore, we document similar patterns of subjective beliefs among parents about their child's prospects.[6]

This paper proceeds as follows. Section 2 overviews our empirical findings, Section 3 lays out the model, and Section 4 describes the model parameterization. Section 5 presents model validation and loan utilization results, and introduces the concept of "over-enrollment". Section 6 reports the

[5]Related work that instead studies regulation of the credit card market includes Nakajima (2012, 2017), which incorporates time-inconsistent preferences, and Exler, Livshits, MacGee, and Tertilt (2021), which allows for optimism about earnings.

[6]Previous structural studies that consider subjective beliefs in the context of post-secondary education have examined grant and tax progressivity policy (Matsuda, 2020, 2022), extrapolating from the empirical findings of Stinebrickner and Stinebrickner (2012) about college students at one U.S. college in order to motivate optimism in the model's population of potential college students along multiple margins. In addition to our empirical contributions described in the main text, we differ in that our focus is on federal student loan policy.

results of our main experiment, and Section 7 concludes.

2 Data

The two main datasets we draw on are the 1997 National Longitudinal Survey of Youth and the High School Longitudinal Study of 2009. Both of these surveys are collected within the United States.

The NLSY97 is a nationally representative panel survey that follows young adults born between 1980 and 1984 ("sample members") from 1997 until the present. It is collected by the U.S. Bureau of Labor Statistics (Bureau of Labor Statistics, U.S. Department of Labor, 2019). The NLSY97 provides information on expected probabilities of earning a 4-year bachelor's degree for sample members and their parents, as well as realized college education outcomes ("college" refers to a 4-year bachelor's degree throughout this paper). We use this information to quantify the extent to which expectations predict college enrollment, and to compare expected college degree attainment probabilities with realized college graduation rates.

The HSLS:09 is a nationally representative panel survey that follows a sample of ninth-grade students from 2009 until 2016, although some information from post-secondary transcripts and student records is collected after 2016; most sample members graduate from high school in the spring of 2013. This survey is conducted by the National Center for Education Statistics (NCES), a subsidiary of the U.S. Department of Education (National Center for Education Statistics, U.S. Department of Education, 2020a). The HSLS:09 contains demographic information collected from sample members and their parents, as well as on student loan balances (if any) collected from student records provided by post-secondary institutions. A useful feature of this data is that the HSLS:09 cohort interacted with the most recent iteration of U.S. financial aid policy (e.g., borrowing limits set in 2012). Accordingly, in this section we use the HSLS:09 to document student loan uptake and balances by college persistence (dropout) status among college enrollees.

2.1 Beliefs about the likelihood of bachelor's degree attainment

The NLSY97 asks sample members at most twice about their expected probability of earning a BA by age 30: once in 1997 and again in 2001. The survey also asks parents the same question about their child, but only once, in 1997. This question can be paraphrased as: "What is the percent chance that [you/your child] will have a four-year college degree by the time [you/they] turn 30?" The response is a percentage which can be any integer between 0 and 100. In both the youth and parent questionnaire, questions about expectations are prefaced by a short orientation statement in which the interviewer explains what probability values communicate qualitatively (Bureau of Labor Statistics, U.S. Department of Labor, 2012b,a). For our main exercises, we use the most recent valid response to this question collected while the sample member was enrolled in high school. The NLSY97 also collects information on college enrollment and degree attainment over the course of the panel; we use these variables to restrict attention to individuals who graduated high school by age 30. We also use these variables to flag those who enrolled in a BA program, and those who earned a BA degree, by age 30. Finally, to measure sample member skill, we use the percentile score of the computer-administered Armed Services Vocational Aptitute Battery score (ASVAB, administered in the 1997 round) after dividing the relevant variable by 1000 so that it takes values between 0 and 100 (Bureau of Labor Statistics, U.S. Department of Labor, 2024). Our sample cleaning procedure is described further in Appendix A.1.1.[7]

How are sample member expected likelihoods of earning a BA related to other demographic attributes of the respondent and their college enrollment decision? To investigate this, in Table 1 we report summary statistics for all high school graduates (Panel A) and the subgroup of high school graduates who enroll in a 4-year BA program by age 30 (Panel B). Using the value of the educational attainment probability question, each sample is also separated into three groups by reported expected probability of earning a BA collected while the respondent is in high school (0 to 32, 33 to 66, or 67 to 100).

In Panel A, the sample of high school graduates has a 54 percent college enrollment rate by age 30; the average expected likelihood of earning a BA is 78 percent, but only 35 percent of sample members earn a BA. The average ASVAB score is 50; 54 percent of the sample is female; the average age when beliefs are collected is about 16, and average age in 1997 is about 15. Parental income in 1997 is about $76,261 in 2016 dollars, corrected for inflation using the Consumer Price Index or CPI (BLS, 2021); the share of high school graduates who have at least one parent with a BA or higher is 0.29. Comparing across belief bins (columns 2 through 4), the low-expectation group has lower college enrollment and college attainment rates, as well as lower skill, fewer women, lower parental education, and lower parental income compared to their high-expectation peers. Among high school graduates, 74 percent reported an expected probability of earning a BA by age 30 in the top belief bin, indicating that beliefs in the population are skewed towards high probabilities.

In Panel B, those who enroll in a BA by age 30 have higher expected graduation likelihoods overall, driven by a greater share of the sample coming from the high-belief bin in the conditional sample. Of course, the realized college attainment rate is also higher among college enrollees than the general population, which narrows the gap between beliefs about the probability of BA attainment and

[7] All tabulations of NLSY97 data do not use survey weights, following Abbott, Gallipoli, Meghir, and Violante (2019).

realized BA attainment rates. Nevertheless, the gap between the expected probability of earning a BA and the realized BA attainment rate among BA enrollees is large: 23.22 percentage points. There is sorting by skill and gender into college enrollment, so that overall and in each beliefs bin the skill level and share who are female is higher than the general population. Parental education and income are also positively associated with enrollment. Finally, the average age in 1997 among those who enroll in college by age 30 is about 15, and the age when beliefs are collected is about 16. Both means are similar to the sample of high school graduates.

These summary statistics indicate that there is a positive correlation between the college enrollment decisions and reported beliefs of survey respondents. College enrollment decisions and expectations are each also correlated with other attributes of the respondent and their parents. However, Table 1 does not establish whether, controlling for other attributes, a higher expected likelihood of BA attainment is associated with a greater likelihood of enrolling in college. This is what we examine next.

Table 1: NLSY97 summary statistics

		Expected probability of earning a BA by 30		
Sample and variable	**All**	**[0,32]**	**[33,66]**	**[67,100]**
Panel A: High school graduates by age 30				
Enrolled BA by 30	54.01 (1.06)	18.96 (2.70)	25.41 (2.28)	64.86 (1.18)
Expected Pr. BA by 30 (student)	78.43 (0.59)	12.55 (0.75)	50.67 (0.28)	93.05 (0.24)
BA by 30	35.15 (1.01)	5.21 (1.53)	11.20 (1.65)	44.32 (1.23)
Skill (ASVAB)	49.91 (0.60)	33.37 (1.70)	35.97 (1.25)	55.14 (0.69)
Female	0.54 (0.01)	0.45 (0.03)	0.47 (0.03)	0.57 (0.01)
Age beliefs response	15.89 (0.02)	15.98 (0.06)	15.92 (0.04)	15.87 (0.02)
Age in 1997	15.14 (0.03)	15.03 (0.10)	15.30 (0.07)	15.12 (0.03)
Real parental income in 1997	76,261 (1,550)	49,960 (3,506)	58,839 (2,586)	83,575 (1,924)
At least one parent BA+ in 1997	0.29 (0.01)	0.09 (0.02)	0.13 (0.02)	0.35 (0.01)
Obs	2,222	211	366	1,645
Sample share	1.00	0.09	0.16	0.74
Panel B: BA enrollees by age 30				
Enrolled BA by 30	100 (0)	100 (0)	100 (0)	100 (0)
Expected Pr. BA by 30 (student)	88.30 (0.58)	11.78 (1.78)	51.53 (0.54)	94.37 (0.27)
BA by 30	65.08 (1.38)	27.50 (7.15)	44.09 (5.18)	68.32 (1.42)
Skill (ASVAB)	62.26 (0.74)	41.37 (3.88)	47.15 (2.55)	64.36 (0.76)
Female	0.58 (0.01)	0.50 (0.08)	0.49 (0.05)	0.59 (0.02)
Age beliefs response	15.87 (0.02)	15.68 (0.10)	15.82 (0.08)	15.88 (0.02)
Age in 1997	15.11 (0.04)	14.98 (0.20)	15.17 (0.13)	15.11 (0.04)
Real parental income in 1997	92,674 (2,421)	53,504 (9,589)	69,074 (6,663)	96,025 (2,606)
At least one parent BA+ in 1997	0.42 (0.01)	0.17 (0.06)	0.24 (0.05)	0.44 (0.02)
Obs	1,200	40	93	1,067
Sample share	1.00	0.03	0.08	0.89

Notes: Table 1 reports summary statistics for the sample of high school graduates (Panel A) and college enrollees (Panel B). Enrollment, youth expectations, and graduation likelihoods are in percentage points. Cell entries are means with standard errors in parentheses; observation counts are for the sample where student attributes are observed; conditioning the sample on also observing parental income or education further restricts the number of observations. Income is in 2016 dollars. Source: NLSY97.

Do beliefs about the likelihood of earning a BA reported in the NLSY97 predict actions? We apply this question to the college enrollment decision in particular, and in Table 2 we report results for a regression in which the dependent variable takes a value of 1 if the individual enrolled in a BA program before age 30 (and is set to 0 otherwise) and the independent variables include the sample member's expected probability of earning a BA degree before age 30, measured while they are enrolled in high school (normalized to be a value between 0 and 1). Additional controls are included: model (1) controls for individual characteristics (i.e., the sample member's skill, an indicator set equal to 1 if the respondent is female and 0 otherwise, and the respondent's age in 1997), while model (2) adds family characteristics (i.e., logged parental income in 2016 dollars and an indicator for having at least one parent with a BA or higher). We use a probit estimator and report Average Marginal Effects (AMEs) in Table 2; regression coefficients for this estimation are presented in Table A1 of Appendix A.1.2.

The results presented in Table 2 indicate that the sample member's expected probability of earning a BA positively predicts college enrollment, even when controlling for individual and family characteristics. Specifically, in model (1) a 1 percentage point increase in the expected probability of earning a BA implies (on average) a 0.425 percentage point increase in the probability of enrolling in a BA program. This effect falls slightly to 0.402 when we control for characteristics of the respondent's family in model (2). In both model (1) and model (2), the AME of beliefs is highly statistically significant.

We draw two additional conclusions from the results of Table 2. First, the fact that beliefs positively predict enrollment after conditioning on skill indicates that there is heterogeneity in beliefs for respondents with the same skill level. Table A2 in Appendix A.1.2 reports a discretized distribution of beliefs conditional on skill in order to quantify this heterogeneity, which we incorporate into the model framework presented in Section 3. Second, because beliefs predict actions, students are not just providing socially desirable answers in their survey response (Krumpal, 2013). Nevertheless, because Table 2 does not rule out that "social desirability bias" may inflate reported expectations in the data, our model parameterization approach of Section 4 allows for such an upward bias in survey responses.

How do expectations about the likelihood of earning a BA compare with reality? Table 3 makes this comparison for three samples of college enrollees. Here, we interpret survey responses as the expected probability of graduation conditional on enrollment in a BA program, whereas in the analysis of Table 2 we remained agnostic on this point. A more general interpretation of the survey's reported expected probability is that it combines the expected probability of enrolling in college with the expected probability of completing college conditional on enrollment, so that $p\,(\text{earn BA}) = p\,(\text{enroll}) \times p\,(\text{graduate} \mid \text{enroll})$. Under this interpretation, for the same reported

Table 2: BA enrollment by age 30 as a function of attributes and beliefs (Average Marginal Effects)

	Enrolled in a BA program by age 30	
Controls	**(1)**	**(2)**
Expected probability of earning a BA by age 30	0.425	0.402
	(0.0316)	(0.0384)
Skill	0.00639	0.00530
	(0.000260)	(0.000348)
Female	0.0578	0.0630
	(0.0181)	(0.0210)
Age in 1997	-0.0110	-0.0148
	(0.00642)	(0.00748)
Logged real parental income in 1997		0.0370
		(0.0122)
At least one parent BA+ in 1997		0.123
		(0.0263)
Obs	2,222	1,606

Notes: Table 2 presents estimated Average Marginal Effects from two probit models. The dependent variable for both models (1) and (2) is an indicator for enrollment in a BA program by age 30, which takes a value of 1 if the individual enrolled in a 4-year program BA program by age 30 and 0 otherwise. The expected probability of earning a BA by age 30 uses respondent beliefs, with a range between 0 and 1. Other controls are described in the main text; both models include a constant. Samples: model (1) is high school graduates; model (2) is high school graduates, conditional on observing parental income and parental education. Standard errors in parentheses. Source: NLSY97.

expected probability of earning a BA (which is what we observe in the data), lowering the expected probability of enrollment that we assume would raise the implied conditional expected probability of graduating once enrolled. In that sense, assuming an expected probability of enrollment of 100 percent, as we do in Table 3, makes our optimism findings lower bounds.

Panel A of Table 3 uses the sample of high school graduates who enroll in college before age 30; it compares respondent expectations with realized graduation rates by skill tercile. We assign each sample member to a skill tercile using the distribution of skill among those who finish high school by age 30. The first column reports the skill tercile; the second column contains the number of observations in each skill tercile for the sample of college enrollees. In the remaining columns we report the within-tercile average, followed by its standard error in parentheses. Specifically, the third column reports the average expected probability of earning a BA by age 30, a value between 0 and 100, using the most recent response collected while the sample member was enrolled in high school. The fourth column contains the realized graduation rates computed as the frequency of BA attainment by age 30, reported as a percentage. The last column reports the percentage point difference between average expected probabilities and the realized probability, which represents the extent of optimism for the skill tercile. The standard errors in this column are computed using the delta method.

Panel A of Table 3 indicates that, within each skill tercile, the expected probability of earning a

BA by age 30 is much higher than the realized rate of attaining that outcome: that is, respondents are optimistic. This is especially true for those with the lowest skill, whose extent of optimism is about 37 percentage points, compared to those with the highest skill, whose extent of optimism is about 15 percentage points.[8]

Table 3: Subjective beliefs of college enrollees

Panel A	**Skill**	**Obs**	(a) **Expected prob. BA by 30**	(b) **Realized graduation rate**	**Difference** $(a)-(b)$
Student optimism by student skill tercile among college enrollees	1	200	80.69 (1.96)	44.00 (3.52)	36.69 (4.03)
	2	416	86.99 (1.05)	58.41 (2.42)	28.58 (2.64)
	3	584	91.84 (0.61)	77.05 (1.74)	14.78 (1.85)
	Obs	1,200			
Panel B	**Response timing**		(a) **Expected prob. BA by 30**	(b) **Realized graduation rate**	**Difference** $(a)-(b)$
Student optimism by response timing among college enrollees	Before enrollment		91.84 (1.03)	73.93 (2.88)	17.91 (3.06)
	After enrollment		93.01 (1.34)	73.93 (2.88)	19.08 (3.17)
	Obs	234			
Panel C	**Skill**	**Obs**	(a) **Expected prob. BA by 30**	(b) **Realized graduation rate**	**Difference** $(a)-(b)$
Parent optimism by student skill tercile among parents of college enrollees	1	136	75.24 (2.30)	41.91 (4.25)	33.32 (4.83)
	2	293	84.23 (1.24)	57.68 (2.89)	26.55 (3.15)
	3	447	90.63 (0.78)	76.06 (2.02)	14.56 (2.17)
	Obs	876			

Notes: Table 3 reports, for each skill tercile, the conditional average of the expected probability of earning a BA by age 30 in column (a), the realized graduation rate in column (b), and the extent of optimism (i.e., a-b) in the last column. Each panel uses a different sample of college enrollees. Panel A compares respondent (student) expectations collected in high school with realized graduation rates by skill tercile for the sample of respondents enrolled in a BA by age 30. Panel B compares student expectations with realized graduation rates by response timing relative to college enrollment (before or after) for the sample of Panel A where respondents also report beliefs in 1997 while in high school and in 2001 having enrolled in a BA before that point. Panel C compares parent expectations of their child's BA attainment likelihood with the realized graduation rates by skill tercile, for the sample of Panel A where the parent expectation response is also observed. Table entries for probabilities contain standard errors in parentheses, computed using the delta method in the last column. Skill terciles are assigned using the distribution of high school graduates. Probabilities are in units of percentages. Source: NLSY97.

Panel A documents optimistic beliefs collected while the respondents are in high school, conditional on their eventually enrolling in a BA program. Does the optimism documented in Panel A

[8] In order to examine whether this pattern is driven by student gender—as research on optimism in other contexts, including stock investment as in Barber and Odean (2001), might suggest—in Table A6 of Appendix A.1.2 we show how the extent of optimism for each skill tercile of college enrollees varies by gender and find that low-skill college students continue to exhibit sizable and relatively higher extent of optimism within each gender grouping. We also examine how the relationship between optimism and skill relates to parent past experience with postsecondary education. Those with low-education parents exhibit monotonicity of optimism in skill. Among those with highly educated parents, young people in the lowest skill tercile exhibit optimism but at a lower magnitude than in the second skill tercile. Nevertheless, so few low-skill college enrollees come from families with at least one highly educated parent that it is not possible to reject monotonicity in that group because standard errors are large.

persist until the college enrollment decision? We argue that it does and offer supporting evidence by examining a group of respondents for whom we can measure educational attainment expectations on both sides of the college enrollment decision. Specifically, we restrict attention to sample members who answer the 1997 question while still in high school and also answer the 2001 question after enrolling in a BA program. The results are shown in Panel B. If these individuals were changing their expectations right before college enrollment to be closer to the realized probability of graduation, then the expected probability after enrolling would be closer to the realized probability of graduating for this group, which is about 74 percent. In fact, the expected graduation likelihood increases slightly from about 92 to 93 percent.[9] The second row of Panel B is the only time we use expectations collected after the sample member is no longer enrolled in high school.

Panel C reports the same statistics as Panel A but for parent expectations about their child's prospects. Compared to Panel A, this panel additionally requires that we observe parents' expected probabilities of their child earning a BA, and the different sample causes the college completion rates by skill tercile to change slightly. Panel C indicates that parents, like their children, are optimistic about their child's prospects for earning a BA, and to a similar extent as their child. In fact, expectated beliefs are very similar within families regardless of college enrollment outcomes for the child, as shown in Table A3 of Appendix A.1.2.

Next, we turn to the sample of those who never enroll in college. We tabulate this group seperately from those who enroll in college because we do not directly observe college graduation rates for non-enrollees; Table 4 compares the average expected probabilities of those who never enroll with the realized graduation rates of those who enroll in each skill tercile, drawn from Table 3. The results in Table 4 make it evident that in the NSLY97 optimism is present and sizable for the lowest levels of skill regardless of college enrollment outcomes.[10]

To summarize, we have presented evidence for optimism about BA attainment, especially for those with low skill levels. We interpret this as evidence for optimism about graduation likelihood. As mentioned above, for our purposes this is a conservative interpretation of the data. Furthermore, Table A7 of Appendix A.1.2 shows that a large share (28 percent) of high school graduates enroll in college and report that their likelihood of BA attainment is 100 percent. The realized graduation

[9]Panel B of Table 3 is not broken down by skill tercile due to small sample size. The sample size is small because a low proportion of respondents meet the education timing criteria and in 2001 only a subset of respondents were asked about educational attainment expectations. The point estimates for average expected and realized probabilities in Panel B of Table 3 differ from those of Panel B of Table 1 because of differences in the samples from which they are computed.

[10]We refrain from interpreting the negative optimism value in Table 4 as pessimism, because our imputation procedure may lead to conditional graduation rates for non-enrollees that are biased upwards. For example, this could be because some non-enrollees have preferences (not taken into account in our imputation) that lower the likelihood of graduation conditional on enrollment. Note, however, that this upward bias in imputed graduation rates implies a lower bound for the extent of optimism that we measure among non-enrollees.

Table 4: Subjective beliefs of non-enrollees

Skill	**Obs**	(a) **Expected prob. BA by 30**	(b) **Realized† graduation rate**	**Difference** $(a)-(b)$
1	542	65.42 (1.37)	44.00 (3.52)	21.42 (3.11)
2	327	66.47 (1.71)	58.41 (2.42)	8.06 (3.12)
3	153	72.59 (2.31)	77.05 (1.74)	-4.47 (3.60)
Obs	1,022			

Notes: Table 4 reports the conditional average of the expected probability of earning a BA by age 30 in column (a), the realized graduation rate for enrollees in the same skill tercile in column (b), and the extent of optimism among non-enrollees (i.e., a-b), broken down by skill tercile. The column (b) † flags realized graduation rates from Panel A of Table 3. Standard errors are in parentheses, computed using the delta method in the last column. Skill terciles are assigned using the distribution of high school graduates. Probabilities are in units of percentages. Source: NLSY97.

rate for this group is 69 percent, implying optimism of 31 percentage points. For this group, it must be that both their expectation to attend a BA program and the expectation to graduate conditional on attending are 100 percent. Therefore, this population is not subject to the concern of our (conservative) interpretation of evidence on optimism about BA attainment as evidence of optimism about college graduation likelihood. The findings of Table A7 directly imply optimism about graduation likelihood. We also show supporting evidence for our optimism findings in the NLSY97 from an additional dataset, the HSLS:09, in Table A16 of Appendix A.2.2. However, our main findings from the HSLS:09 relate to student loans, and in the next section we use that dataset to document how uptake of student loans varies by college persistence status.

2.2 Student loan uptake and balances by persistence status

Using the HSLS:09, we restrict our sample to students who earn a high school diploma by the summer of 2013 and enrolled in a BA program in the fall of 2013; details of our sample cleaning procedure are provided in Appendix A.2.1. We then assign a persistence status to each enrollee in the sample. By "persisting," we mean maintaining enrollment in the BA program from their first year (the 2013-2014 academic year) through their third year (the 2015-2016 academic year). An enrollee who does not persist leaves college for at least one academic year over this period. Persistence status is the empirical measure of dropout that we are able to construct in this dataset, given the short panel dimension of the HSLS:09.

How do student loan uptake and balances vary by college persistence status? Table 5 addresses this question by reporting student loan statistics by persistence status. The results indicate that, of all enrollees, 24 percent fail to persist toward college completion; those who do not persist owe 19 percent of the sample's federal student debt balances and are just as likely to have student debt relative to those who persist. Conditional on having debt, the average and median loan balance is economically significant several years after enrollment, regardless of persistence status. This is true despite non-persisters using that money to finance fewer years of tuition, compared to students who persisted.[11]

Table 5: Federal student loan incidence by persistence status

Persistence status	% of enrollees	% of SL $	% with SL	Average $	Median $
Did not persist	24	19	77	10,795	9,500
Persisted	76	81	64	17,250	18,499
Obs	2,356				

Notes: Table 5 groups 2013 bachelor's degree enrollees into students who persisted in college and those who did not persist. For each group, the table reports the group's percentage of enrollees, the dollars owed by the group as a percentage of aggregated federal student debt among enrollees, the percentage of the group with a positive federal student debt balance, and the average and median federal student loan balance owed by debtors in the group after three academic years in 2016 dollars. Persistence status status is assigned as described in the text. Percentages are rounded to the nearest percentage point. Weights are PETS-SR student records longitudinal weights. Source: HSLS:09.

In the next section, we build a model framework that incorporates our empirical findings from Section 2.1 on subjective beliefs. Our findings on student loan uptake in Section 2.2 are used to validate the calibrated model in Appendix C.

3 Model

Motivated by our findings in Section 2.1, we enrich the general equilibrium life cycle model with college choice of Krueger and Ludwig (2016) by incorporating subjective beliefs about the likelihood of college graduation. We also incorporate endogenous and exogenous college dropout, as in Chatterjee and Ionescu (2012), and key features of the federal student loan program based on Luo and Mongey (2019).

In Section 3.1, we provide an overview of the model along with the notation necessary for the main value functions, presented in Section 3.2. Section 3.3 presents the functional forms. The remaining value functions, the equilibrium definition, and the computational algorithm are presented in Appendix B.1, B.2, and B.3, respectively. In this section, we present the baseline model. In

[11] Our findings documenting student debt among non-persisters in the HSLS:09 complements the work of Chatterjee and Ionescu (2012), which uses the SCF to show that outstanding balances held by college dropouts are significant. We expand this analysis in two ways and reach similar conclusions. First, we use the HSLS:09 to document significant balances among non-persisting enrollees by tracking a single cohort of college students until three academic years after enrollment. These attributes are an advantage compared to a cross-sectional sample like that of the SCF, with the potentially large heterogeneity in federal policy regimes at loan issuance, time in repayment, labor market experience, and other factors that such a sample implies. Second, information in the HSLS:09 on student debt balances is drawn from student records submitted by post-secondary institutions, which are likely to be a more reliable source of information than self-reported balances recorded in the SCF.

Appendix D.4, we consider several sensitivity analyses in which we modify and re-calibrate the baseline model and re-run our main experiments.

3.1 Overview

Time is discrete and runs forever; each period lasts one year. There are three main types of agents in the economy: consumers, the government, and a final goods firm.

Consumers Let j denote the age of consumers; consumers start making decisions when they turn 18 at $j = 1$. Figure 1 illustrates the phases of the consumer's adult life cycle.

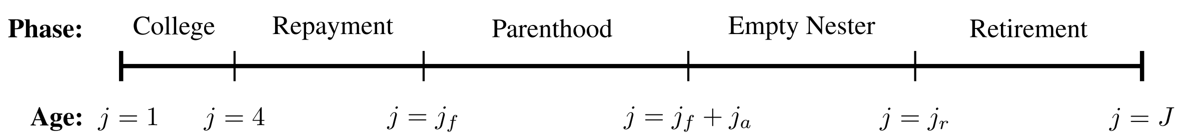


Figure 1: Phases of the consumer's life cycle

Let s denote the skill endowment; at the start of adulthood, with an exogenous probability $q(s)$, 18-year-old consumers may choose whether to enroll in college; otherwise, college is not an option, and they join the workforce without a college degree.[12] The enrollment decision depends on the skill endowment as well as an idiosyncratic earnings productivity, η, initial net assets, a, and the subjective belief about the annual probability of being allowed to continue in college, $\hat{p}$. The skill endowment is drawn once and indexes the distribution from which the consumer's subjective belief is drawn at the start of adulthood, the true probability of being allowed to continue given enrollment, the deterministic component of earnings, and Social Security transfers. The idiosyncratic productivity component of earnings follows a lag-1 auto-regressive, or AR(1), process that depends on completed education. Net assets at the start of adulthood are determined by a one-time inter vivos transfer from the consumer's parent. In our notation, $a \geq 0$ represents positive net assets earning an interest rate r, whereas $a < 0$ represents federal student loan balances.

Earning a college degree requires four completed years of enrollment. Consumers learn their true annual probability of being allowed to continue in college, denoted by $p(s)$, immediately after enrollment; they may then choose to leave college any time after their first academic year.[13]

[12] This model feature captures academic, personal, or family reasons that prevented college enrollment (see Table A14 in Appendix A.2.2 for suggestive empirical evidence). Conceptually, this modeling approach is a nested version of stochastic utility costs, where with probability $1 - q(s)$, the realized cost draw is large enough to prevent enrollment.

[13] The choice to model skill as the determinant of the true annual probability of being allowed to continue in college is motivated by our empirical findings presented in Table A15 in Appendix A.2. The findings of Table A15 indicate that skill is the key predictor of continuation in college enrollment. As for attributing this role (at least partly) to an exogenous shock, we build on the findings of Stinebrickner and Stinebrickner (2012), which show that heterogeneity in ability, rather than heterogeneity in effort, leads to college dropout. For example, even for students in the same

Education is recorded with e; a college student or college graduate has a high level of education, indicated with $e = h$, although only a college graduate enjoys the college wage premium. If the consumer never enrolls, or drops out of college, then they have a low level of education and e is set to ℓ.

Figure 2 depicts the college phase for an 18-year-old who decided to enroll given their initial state $(s, \eta, a, \hat{p})$, shown in the "State" row at the top of the figure. The thick black arrow traces the already-realized path of this fictional student; the figure shows the student's possible paths at the end of their first academic year, after they have learned their true probability of being allowed to continue but before they know if they will have the option. In the figure, possible outcomes for this draw are indicated by the orange arrows. At this point, besides age j, their state space reflects the education choice, and includes skill, AR(1) earnings productivity, and net assets or federal student loans: $(j, e = h, s, \eta, a)$. The initial belief about the likelihood of being allowed to continue, $\hat{p}$, is dropped from the state space because the student learns their true annual probability of being allowed to continue after enrollment. Not being allowed to continue enrollment generates exogenous dropout, which represents being forced to leave because of a lack of academic ability. If allowed to continue, the student may also choose to endogenously drop out at the start of the next academic year (dotted blue arrow). Although not shown in the figure, in the model a college enrollee faces a similar situation at the end of each academic year of college—the only difference being that after year 4 there is no choice to continue after the continuation shock is realized, because the student has graduated.

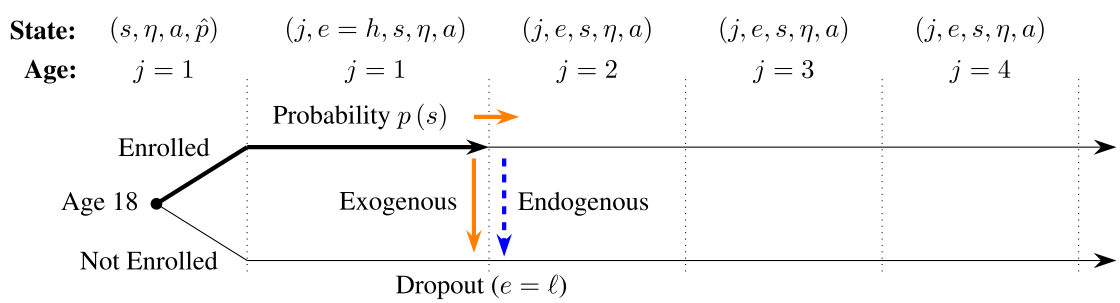


Figure 2: The college phase

Notes: The top two rows of Figure 2 indicate the period's state space and age, respectively. The thick black arrow traces the path of a consumer who enrolls at 18 ($e = h$ and model age $j = 1$). At the end of the first academic year with probability $p(s)$ this enrollee is allowed to continue to the second academic year; otherwise, they exogenously drop out (solid orange arrows). If allowed to continue, consumers may choose to endogenously drop out (dashed blue arrow).

The benefits of graduating from college are higher labor earnings, higher Social Security transfers,

major who put in the same hours of study, the paper finds significant differences in academic performance, which is a key predictor of college dropout.

and a consumption value of college.[14] The costs of college are foregone earnings due to part-time work (ℓ_{pt}), an annual pecuniary cost (tuition and fees, κ), and an effort cost (λ). The effort cost is net of any consumption value of college and is captured by a utility shifter. College expenses including room and board can be financed with student loans borrowed from the federal student loan program, as well as inter vivos transfers from parents, grants from public and private sources, and earnings from part-time work. Let $\bar{A}$ denote the fraction of annual net tuition and fees plus room and board expenses that the federal student loan limit is sufficient to finance, and θ and θ^{pr} denote the share of tuition and fees paid for by public and private grants, respectively.

After the age of college graduation, consumers with an outstanding student loan balance may be either college graduates or college dropouts; student debt is the only form of debt in the economy. After the age of college graduation, consumers begin to make decisions on whether to make loan payments: in particular, they choose between repayment, $d_f = 0$, and delinquency, $d_f = 1$.[15] Upon paying off student loans, consumers solve a standard consumption-savings problem by choosing consumption, c, and next periods net assets a'.[16] Consumers who choose repayment must make a payment of at least $\rho_R(j, a)$. Consumers who do not make payments on their student loans are considered delinquent, and their disposable income above a threshold $\bar{y}$ is garnished. In the period they are delinquent, these debtors also incur a collection fee determined by the parameter ϕ_D, and a utility cost, ξ_D.

All consumers have a child at the fertile age, j_f; this child will leave the household j_a years after birth. At the beginning of the period when the child leaves, as in Krueger and Ludwig (2016) and Abbott, Gallipoli, Meghir, and Violante (2019), each parent makes an inter vivos transfer, b, to their child after observing the child's skill, s_c, and the subjective belief about the child being allowed to continue in each year of college, $\hat{p}$. Note that the subjective belief is the same for the parent and their child. Inter vivos transfers are motivated by parental altruism, where the intensity is determined by a child lifetime utility discount factor, β_c. The conditional probability over subjective beliefs is denoted by $\pi_{\hat{p}}(\hat{p}|s_c)$; child skill is assumed to be uniformly distributed across skill endowments and this probability is denoted by $\pi_{s_c}(s_c)$.

[14] Consumers must graduate from college to enjoy the benefits of higher labor earnings and Social Security transfers. Table A11 of Appendix A.1.3 shows that relative to having only a high school degree the marginal effect of some college (college dropouts or those with an associate's degree) on the age profiles of earnings is approximately zero.

[15] In our model, it is not possible to have the federal student loan debt written off via default. This is consistent with U.S. policy, where student loans may eventually be classified as defaulted loans but are almost never discharged.

[16] We assume that student loans must be paid off for consumers to save because this reduces the state space necessary to represent asset and debt positions from two to one elements. This assumption is consistent with optimizing behavior by the consumer in an environment in which consumers cannot be delinquent, because in that case, the optimal strategy would be to pay off loans before saving as long as the interest rates on loans are higher than the savings interest rate. The interest rates are ordered in this way in our framework by construction. This incentive might be somewhat offset because of the delinquency choice we incorporate, but that is not a quantitatively significant concern.

Consumers retire at age j_r. At this point, they stop working and receive Social Security transfers. Consumers survive each period with probability ψ_j, and live for a maximum of J periods. The assets of the dead are re-distributed to consumers as accidental bequests, Tr_j, which depends on age.

The subjective beliefs discussed thus far imply that consumers in our model deviate from rational expectations in the following way: 18-year-olds making the college enrollment decision (and their parents choosing inter vivos transfers) believe that they are unique when it comes to their probability (or their child's probability) of being allowed to continue from one academic year to the next. Consumers understand everything else about their environment: they know their own skill, how skill affects earnings, and that others have subjective beliefs. Because individuals are atomistic, they can believe that their own continuation probability is uniquely different from others of the same type, while taking as given aggregate endogenous states which are computed using decision rules of consumers with subjective beliefs and then simulated with the true continuation probabilities. Consumers in this model will have rational expectations if $\hat{p} = p(s)$ for all s.

Government The federal student loan program is characterized by an annual student loan limit $\bar{A}$ and a student loan interest rate $r_{SL} = r + \tau_{SL}$, where r is the risk-free interest rate on savings and τ_{SL} is the add-on set by the government. In our main experiment, to expand the federal student loan limit, we increase $\bar{A}$ from its baseline value. Federal student loans are assessed interest starting from the year after the age of college graduation ($j > 4$).

In addition to running the federal student loan program, the government provides grants for college education and funding for Social Security, and also faces an exogenous government consumption requirement expressed as a fixed fraction g of gross domestic product (GDP). Expenditures are financed with revenue generated from a flat-rate consumption tax, τ_c, and progressive income taxes. Let $y_{j,\ell,s,\eta,a}$ denote pretax income, which is a function of age, completed education, skill, the AR(1) productivity component, and net assets. $T(y)$ denotes the income tax function.

Final goods firm Output is produced by a final goods firm, which operates a production technology in which the inputs are capital, efficiency units of low-education labor, and efficiency units of high-education labor.

3.2 Consumer life cycle problem

Consumer problems before college graduation age (j ≤ 4) Given their type, $(s, \eta, a, \hat{p})$, which reports skill, idiosyncratic AR(1) productivity, net assets, and the subjective belief about being allowed to continue in each of year of college, respectively, an 18-year-old (age $j = 1$) has an expected value given by

$$\hat{W}(s,\eta,a,\hat{p}) = q(s)[\max_{\hat{d}_e}(1-\hat{d}_e)V(j=1,\ell,s,\eta,a)+\hat{d}_e\hat{V}(j=1,h,s,\eta,a,\hat{p})]+ \\ (1-q(s))V(1,\ell,s,\eta,a) \tag{1}$$

With probability $q(s)$, the consumer may choose whether to enroll in college by choosing $\hat{d}_e \in \{0,1\}$, where $V(j=1,\ell,s,\eta,a)$ is the value of not going to college and $\hat{V}(j=1,h,s,\eta,a,\hat{p})$ is the value of going to college given subjective beliefs about being allowed to continue in college (hereafter referred to as the subjective value of college). With exogenous probability $1-q(s)$, the consumer does not have the option to enroll and proceeds through life as a low-education worker. The value of not going to college or dropping out for $j \leq 4$ is given by

$$\begin{aligned} V(j,\ell,s,\eta,a) &= \max_{c\geq 0,a'} U(c,j,\ell)+\beta\psi_j E_{\eta'|\ell,\eta}V(j+1,\ell,s,\eta',a') \\ & s.t. \\ & (1+\tau_c)c+a' = y_{j,\ell,s,\eta,a}+a+Tr_j - T(y_{j,\ell,s,\eta,a}) \\ & a' \geq \min[a,0] \end{aligned} \tag{2}$$

where $U(\cdot)$ is the utility function and β is the discount factor. College dropouts solving (2) cannot accumulate debt beyond their outstanding stock of student debt. For consumers who never enroll in college, net assets are always weakly positive because student loans are the only form of borrowing. When making the college enrollment decision, the subjective value of college for $j=1,2,3$ is given by

$$\begin{aligned} &\hat{V}(j,h,s,\eta,a,\hat{p}) = \max_{\hat{c}\geq 0,\hat{a}'} U(c,j,h)+ \\ &\beta\psi_j E_{\eta'|\ell,\eta}\big[\hat{p}\max[\hat{V}(j+1,h,s,\eta',\hat{a}',\hat{p}),V(j+1,\ell,s,\eta',\hat{a}')]+(1-\hat{p})V(j+1,\ell,s,\eta',\hat{a}')\big] \\ & s.t. \\ &(1+\tau_c)\hat{c}+\hat{a}'+(1-\theta-\theta^{pr})\kappa = y_{j,h,s,\eta,a}+a+Tr_j - T(y_{j,h,s,\eta,a}) \\ &\hat{a}' \geq -\bar{A}j[(1-\theta-\theta^{pr})\kappa+\bar{c}] \end{aligned} \tag{3}$$

These consumers may choose to drop out before the start of the next academic year, which is captured by the "max" expression in the continuation value. College students can borrow from federal student loans subject to the limit determined by $\bar{A}$; the multiplier j is an adjustment for the fact that the cumulative limit increases with each year of college.[17] The subjective value for

[17] Room and board expenditure, $\bar{c}$, is not a mandatory expenditure in our model because most students live off campus in practice, as shown in NCES (2020b). An amount for room and board expenditure is included in the limit for

the final year of college, when $j = 4$, is presented in equation (15) in Appendix B.1. When constructing this value, the post-college continuation value conditional on graduation is based on $E_{\eta'|h,\eta}$ rather than $E_{\eta'|\ell,\eta}$. Furthermore, no endogenous dropout decision will be made in the continuation value because in the next period, the consumer will have graduated from college. The rest of the value function for the final year of college remains unchanged from previous years.

When consumers make the college entrance decision in equation (1), they have subjective beliefs and will use the subjective value of college from (3) to compute their expected value. This is why $\hat{p}$ is included as a state variable in equations (3) and (15). However, consumers learn the true probabilities of being allowed to continue in the first year of college so that, while enrolled, the consumer's realized consumption-savings and dropout decisions are based on the following value function for $j = 1, 2, 3$:

$$V(j,h,s,\eta,a) = \max_{c\geq 0,a'} U(c,j,h) + \tag{4}$$
$$\beta\psi_j E_{\eta'|\ell,\eta}\big[p(s)\max[V(j+1,h,s,\eta',a'),V(j+1,\ell,s,\eta',a')] + (1-p(s))V(j+1,\ell,s,\eta',a')\big]$$

where the control variables and constraints (omitted for the purpose of exposition) for this value function are the same as in the subjective value function given by (3), but without the hats. The only difference between this value function and the subjective value function is that (4) incorporates true probabilities of being allowed to continue in each year of college, $p(s)$, rather than the subjective belief probability, $\hat{p}$. Again, in the final year of college ($j = 4$), the consumer's value of college will be computed using an equation that is similar to equation (15) in Appendix B.1, with the exception that the consumer will use the true probability of being allowed to continue rather than the subjective belief about being allowed to continue in each year of college.

Consumer problems after college graduation age (j $>$ 4) Consumers begin student loan payments the year after college graduation age, regardless of whether they complete college. For the remainder of this section, we focus on the parent's problem of choosing between repayment and delinquency and their value of repayment at age $j_f + j_a$, the age at which they make an inter vivos transfer. Timing within this period is as follows. At the start of age $j_f + j_a$, the parent draws their child's type and the family's subjective belief and then chooses whether or not to be delinquent on

federal student loans so that $\bar{A}$ represents the fraction of annual college expenditure that student loans are enough to pay for.

loan payments. The value function before the draw of child skill and subjective belief is given by

$$V(j,e,s,\eta,a) = \sum_{s_c} \pi_{s_c}(s_c) \sum_{\hat{p}} \pi_{\hat{p}}(\hat{p}|s_c) \,[\, \max_{d_f \in \{0,1\}} (1-d_f) V^R(j,e,s,\eta,a,s_c,\hat{p}) + \tag{5}$$
$$d_f V^D(j,e,s,\eta,a,s_c,\hat{p}) \,]$$

The terms $V^R(\cdot)$ and $V^D(\cdot)$ denote the value of repayment and the value of delinquency, respectively. Here, we show the value of repayment for $j = j_f + j_a$, given by

$$V^R(j,e,s,\eta,a,s_c,\hat{p}) = \max_{c \geq 0, a', b \geq 0} U(c,j,e) + \beta \psi_j E_{\eta'|e,\eta} V(j+1,e,s,\eta',a') + \beta_c E_{\eta'|\ell} \hat{W}(s_c,\eta',b,\hat{p})$$
$$s.t. \tag{6}$$
$$(1+\tau_c)c + a' + b = y_{j,e,s,\eta,a} + a + r_{SL} a \mathbb{I}_{a<0} + Tr_j - T(y_{j,e,s,\eta,a})$$
$$a' \geq \min[(1+r_{SL})a + \rho_R(j,a), 0]$$

Because the parent uses $\hat{W}(\cdot)$ for their child's lifetime utility, the parent also has the same subjective belief as their child about the likelihood of the child being allowed to continue in college. The child's AR(1) productivity η' is drawn from the stationary distribution for a consumer without a college degree. The constraint on a' implies that if the consumer has student loans and chooses repayment, they must at least pay off the full repayment amount for that period given by $\rho_R(j,a)$.

3.3 Functional forms

Student loan payments The full payment function for federal student loans is given by

$$\rho_R(j,a) = \begin{cases} -\dfrac{r_{SL}}{1-(1+r_{SL})^{-(T_{SL}+5-j)}} a & \text{if } a<0 \text{ and } 4<j \leq T_{SL}+4 \\ -(1+r_{SL})a & \text{if } a<0 \text{ and } j > T_{SL}+4 \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

If there is an outstanding balance and j is still within the standard repayment period, T_{SL}, the loan is amortized with an interest rate of r_{SL}; if there is an outstanding loan balance and the standard repayment period has expired, the outstanding principal plus interest is due; and, if there is no outstanding loan balance, the payment amount is zero. Instead of repayment, if a consumer chooses delinquency, their disposable income above $\bar{y}$ is garnished at the rate τ_g. This leads to a partial payment function given by

$$\rho_D(j,a,y) = \min[\tau_g \max[y - T(y) - \bar{y}, 0], \rho_R(j,a)] \tag{8}$$

where the garnishment amount is bounded above at the full payment amount $\rho_R(j,a)$.

Preferences A consumer's utility depends on total household consumption, c, the consumer's age, j (which determines whether or not they have a child), and their education status, $e \in \{h, \ell\}$. It is given by

$$U(c,j,e) = \frac{\left(\frac{c}{1+\zeta \mathbb{I}_{j\in\{j_f,..,j_f+j_a-1\}}}\right)^{1-\sigma}}{1-\sigma} - \lambda \mathbb{I}_{e=h \text{ and } j\in\{1,2,3,4\}} \tag{9}$$

Together with j, e identifies whether or not a consumer is in college. Utility exhibits constant relative risk aversion over per-capita household consumption, with a relative risk aversion given by σ. When the child lives with the parent, $j \in \{j_f, .., j_f + j_a - 1\}$, the child is included in total household consumption with an adult equivalence parameter ζ. College students, for whom $e = h$ and $j \in \{1,2,3,4\}$, are subject to an effort cost net of college consumption value.

Income Age, education, skill, stochastic earnings productivity, and net assets, summarized by the tuple (j, e, s, η, a), determine income, y, given by

$$y_{j,e,s,\eta,a} = [w_\ell \epsilon_{j,\ell,s} \ell_{pt} \mathbb{I}_{j\le 4} \mathbb{I}_{e=h} + w_e \epsilon_{j,e,s} \mathbb{I}_{j>4 \text{ or } e=\ell} \mathbb{I}_{j<j_r}]\eta + ss_{e,s}\mathbb{I}_{j\ge j_r} + r\left[a\mathbb{I}_{j>1}\mathbb{I}_{a>0} + Tr_j\right] \tag{10}$$

where w_e is the wage rate that depends on completed education, $\epsilon_{j,e,s}$ is the deterministic component of earnings that depends on age, completed education, and skill, and $ss_{e,s}$ is the Social Security transfer that depends on completed education and skill as defined in equation (20) in Appendix B.2.[18]

Income tax The income tax function follows the specification from Heathcote, Storesletten, and Violante (2017) and is given by

$$T(y) = y - \gamma y^{1-\tau_p} \tag{11}$$

where τ_p governs the tax progressivity and γ is used to balance the government budget constraint in every period as shown in equation (22) in Appendix B.2.

Technology The production function for output uses capital and aggregate labor in Cobb-Douglas form, and is given by

$$Y = K^\alpha (ZL)^{1-\alpha} \tag{12}$$

where K is aggregate capital stock, Z is aggregate labor productivity, L is aggregate labor, and α is the capital share. The capital stock depreciates at rate δ. Aggregate labor is a composite of

[18]The indicator $\mathbb{I}_{j>1}\mathbb{I}_{a>0}$ implies that interest income on the inter vivos transfer accrues to the parents and not the newly emancipated child aged $j = 1$. This is a neutral assumption about timing: If the interest accrued to the child instead, the parent simply would choose an alternative b so that the net amount transfered to the child was the same.

efficiency units of labor with low education, L_ℓ, and efficiency units of labor with high education, L_h, given by

$$L = (\nu L_\ell^\iota + (1-\nu)L_h^\iota)^{1/\iota} \tag{13}$$

where $1/(1-\iota)$ is the constant elasticity of substitution and ν is a share parameter.

4 Model Parameterization

The parameters of this model are divided into those estimated outside of the model, shown in Tables 6 and 7, and those calibrated inside of the model, shown in Table 8.

Table 6 presents externally estimated parameters related to education. The first column reports the parameter's symbol; the second column describes the parameter; the third colulmn provides the data source, and the fourth contains the parameter's value. Panel contains a set of federal student loan policy parameters set to statutory values and the student loan collection fee, set to an estimate from the literature, while parameters in Panels B, C, and D are disciplined using our estimation results.

Panel A begins with the annual federal student loan limit, $\bar{A}$, which is set to the annualized current cumulative borrowing limit for four years of college; the second row contains the number of years for repayment on a student loan, T_{SL}. Both values are drawn from a Congressional Research Service report (Smole, 2019); the former value is normalized by the sum of average annual net tuition and fees and average room and board drawn from the Department of Education statistical report NCES (2019) and the College Board report Ma, Pender, and Libassi (2020).[19] Next is the add-on for the federal student loan interest rate, τ_{SL}, which is set to the most recent value as reported by Chief Operating Officer for Federal Student Aid (2021). The garnishment rate conditional on delinquency for student loans, τ_g, is set to match the statutory value in the 2005 Deficit Reduction Act (109th Congress of the United States of America, 2006). Lastly, the student loan collection fee, ϕ_D, is set to the value of Luo and Mongey (2019).

The first two rows of Panel B of Table 6 report the estimated share of tuition and fees paid with grants and scholarships from public sources, θ, and private sources, θ^{pr}. To assign these values, we first use data from the HSLS:09, reported in Table A13 of Appendix A.2.2, to compute aggregate grants from any source as a share of aggregate tuition and fees. We then multiply the total share of

[19]The borrowing limit has been in place since July 1, 2012. The U.S. federal student loan program sets a borrowing limit for each academic year (e.g., freshmen) and dependency status as well as a lifetime limit. In our parameterization, we assume that borrowers are dependents because most undergraduate students are less than 24 years old, and use the cumulative limit over the first four years because college in our model lasts for four years. For the repayment period, in the U.S. those with student loans may choose between a standard repayment plan of 10 years and an income-based repayment plan, which may have a repayment time frame ranging from 10 to 25 years.

tuition subsidized by grants by 0.7 to assign values to θ and assign the residual to θ^{pr}, incorporating estimates from Krueger and Ludwig (2016) on grants from public versus private sources. The third row of Panel B reports working hours while in college, ℓ_{pt}, which we estimate using the average hours worked per week, expressed as a fraction of full-time work, for third-year college students in the HSLS:09 as reported in Table A14 in Appendix A.2.2.

Panel C of Table 6 begins with the deterministic component of the life cycle earnings profile, represented by $\epsilon_{j,e,s}$. The next two rows are the AR(1) persistences ρ_e and variances σ_e^2, respectively, which have one value for each education status. In Appendix A.1.3, we specify the functional forms of both the deterministic and stochastic components of the life cycle earnings profile and describe how we estimate them using the PSID and NLSY97; we report our full set of results in Table A9.

Table 6: Externally estimated parameters related to education

Symbol	Parameter description	Source	Parameter value
Panel A: Federal student loan program			
$\bar{A}$	Annual limit	Statutory	0.370
T_{SL}	Maximum years to repay		10
τ_{SL}	Interest rate add-on		0.021
τ_g	Federal SL garnishment rate		0.150
ϕ_D	Student loan collection fee	Luo and Mongey (2019)	0.185
Panel B: College grants and working hours			
θ	Public tuition grant subsidy	HSLS:09 and Krueger and Ludwig (2016)	0.346
θ^{pr}	Private tuition grant subsidy		0.148
ℓ_{pt}	Working hours while in college	HSLS:09	0.347
Panel C: Life cycle earnings profile			
$\epsilon_{j,e,s}$	Deterministic component	PSID and NLSY97	Table A9
ρ_e	AR(1) persistence for $e = (\ell, h)$		(0.904, 0.886)
σ_e^2	AR(1) variance for $e = (\ell, h)$		(0.052, 0.072)
Panel D: Distribution of subjective beliefs			
$\pi_{\hat{p}}(\hat{p}\|s)$	Mass in each subjective belief bin	NLSY97	Table A2
$\hat{p}_1(s)$	Annualized subjective belief: probability		(0.437, 0.453, 0.514)
$\hat{p}_2(s)$	of being allowed to continue in college		(0.703, 0.708, 0.704)
$\hat{p}_3(s)$			(0.838, 0.835, 0.840)
$\hat{p}_4(s)$			(0.920, 0.921, 0.921)
$\hat{p}_5(s)$			(0.990, 0.992, 0.990)

Panel D of Table 6 reports parameters governing the conditional distribution of subjective beliefs from which $\hat{p}$ is drawn. Specifically, for each skill bin, we discretize the distribution of beliefs into five bins of equal width (0-19, 20-39, etc.). The mass of responses in each element of this grid, $\pi_{\hat{p}}(\hat{p}|s)$, is estimated directly from the data and is reported in Panel A of Table A2 in Appendix A.1. To estimate the five grid-point values of each conditional distribution, $\hat{p}_1(s)$ through $\hat{p}_5(s)$, we set each annual probability as a value between zero and one so that over four years it is equal to the average expected probability in the same bin measured in the NLSY97, as reported in Panel B of Table A2 of Appendix A.1. In Panel D, the annualized values are reported as a vector (one element for each skill tercile) conditional on the row's belief-value bin.

This parameterization approach implements the following logic. Imagine that one is collecting a “survey" in the model that asks the same question as the NLSY97 about the likelihood of earning a bachelor’s degree. The goal is to construct a model statistic that we map to the data on subjective beliefs. We make two assumptions about the behavior of survey respondents in the model. First, respondents report the likelihood of earning a four-year BA conditional on enrollment. This (conservative) assumption is the same as our treatment of the NLSY97 beliefs data in the discussion of Tables 3 and 4 of Section 2.1. Second, respondents lie in the model survey and over-report the expected likelihood of graduation by ignoring that dropout may arise endogenously. This assumption introduces an upward social desirability bias in the reported graduation likelihoods. Of course, in the model, when 18-year-olds decide whether or not to enroll they incorporate endogenous dropout into their value of college. Only their responses to the model survey are inflated by social desirability bias.

In the discussion of our empirical findings in Section 2.1, we pointed out that the observed difference between expected and realized graduation likelihoods could be inflated by bias in survey responses. The two assumptions that we apply to parameterize subjective beliefs in the model lead to conservative estimates for the true extent of optimism about graduation, which we do not measure directly in the data.[20] In model validation exercises presented in Section 5.1, we show that our mapping of the model to the NLSY97 data on subjective beliefs introduces a reasonable role for reported beliefs in determining college enrollment within the model, compared to our regression results in Table 2. We also show that the model exhibits a reasonable elasticity of enrollment to college tuition subsidies compared to estimates in the literature. In Table A22 of Appendix C, we show that the model matches the extent of optimism by enrollment status and skill tercile in the NLSY97, as reported in Tables 3 and 4. These moments are not targeted in our calibration.

Table 7 presents externally estimated parameters unrelated to education and has the same column structure as Table 6. Panel A parameters are determined by assumption or by using estimates from institutional reports or the literature; by contrast, we estimate Panel B parameters directly from the data.

Panel A begins with parameters related to demographics: the fertility period, j_f, is set so that consumers have a child when they turn 30; the age that children leave to become adults, j_a, is set to 18; j_r is chosen so that the retirement age is 65; and, finally, J sets maximum life span to 100 years. For $j < j_f + j_a$, we set survival probabilities ψ_j to one to rule out children without parents; ages $j \geq j_f + j_a$ use estimates from the 2010 Social Security Administration (SSA) Life Tables reported

[20]In the model, if we shut off endogenous college dropout, a consumer at the time of enrollment is optimistic about graduating college as long as $\hat{p} > p(s)$. With endogenous college dropout, the inequality specified in the previous sentence is a sufficient condition for optimism, but not a necessary condition.

in Bell and Miller (2020). Next, we turn to parameters related to preferences and technologies, starting with the adult equivalence scale, ζ, which is set following the Organization for Economic Co-operation and Development (OECD) modified scale proposed originally by Hagenaars, de Vos, and Zaidi (1994). The relative risk aversion parameter, σ, is set based on Chetty (2006); the capital share parameter, α, is set following Kydland and Prescott (1982); the depreciation rate of capital, δ, is set as in Krueger and Ludwig (2016). The last row of Panel A contains ι, the parameter that dictates the elasticity of substitution between low- and high-education labor, which is assigned to imply an elasticity of substitution of 5. This is in the middle of the range (between 4 and 6) reported in Card and Lemieux (2001) after controlling for imperfect substitutability across age groups. In Appendix D.4, we perform sensitivity analyses for our main experiment with a higher and lower value for this elasticity of substitution.

Panel B of Table 7 contains three government policy parameters not related to education. First, we estimate the value of the consumption tax rate, τ_c, using data from the OECD as reported in Table A20 of Appendix A.4; second, we estimate the progressivity of the income tax function, τ_p, using data from the Congressional Budget Office (CBO) as presented in Table A18 of Appendix A.3; and, third, we estimate government consumption as a share of GDP, g, using data published by the Bureau of Economic Analysis (BEA) in BEA (2022, T1.1.5) and BEA (2022, T3.1).

Table 7: Externally estimated parameters not related to education

Symbol	Parameter description	Source	Parameter value
Panel A: Demographics, preferences, and technology			
j_f	Child bearing age	30 years	13
j_a	Years for child to move out	18 years	18
j_r	Retirement age	65 years	48
J	Maximum life span	100 years	83
ψ_j	Survival probability	2010 SSA Life Tables	-
ζ	Adult equivalence scale	OECD modified scale	0.3
σ	Risk aversion	Chetty (2006)	2
α	Capital share	Kydland and Prescott (1982)	0.360
δ	Depreciation rate	Krueger and Ludwig (2016)	0.076
ι	Elasticity of substitution	Card and Lemieux (2001)	0.800
Panel B: Government policy			
τ_c	Consumption tax rate	OECD	0.043
τ_p	Income tax progressivity	CBO	0.177
g	Government consumption	BEA	0.141

Table 8 reports internally calibrated parameters. The first column contains the parameter symbol; the second column, the parameter description; and the third column, the parameter value. Columns 4 through 6 contain the target moment's description, the moment in the data, and the moment in the calibrated model, respectively. Note that, although parameters and moments are grouped in Table 8 using the most significant one-to-one relationship between each parameter and target moment, and are discussed accordingly, the parameters are calibrated jointly and each parameter can affect all target moments. In several rows within this table, we note with the term "normalized" that the value is normalized by GDP per capita for those 18 and over, which is computed for each year by combining information on GDP from 2016-2018 from BEA (2022, T1.1.5) and population levels found in Census Bureau of the United States (2020).

Panel A of Table 8 presents parameters governed by moments we compute using the NLSY97. The first object is $p(s)$, the true probability of being allowed to continue in each academic year of college, is disciplined using graduation probabilities reported in Panel A of Table 3 in Section 2. We cannot estimate $p(s)$ directly from the data because of the endogenous dropout decision (in our baseline calibration, for a given cohort, total endogenous dropouts are 2.18 percent of total dropouts). Next is the college effort cost net of the consumption value of college, λ, which is determined using the observed college enrollment rate by age 25 in the population (Table A4, Appendix A.1.2). The college enrollment option shock, $q(s)$, is chosen to target enrollment rates for the top parental income tercile for each skill bin (Table A5, Appendix A.1.2). Because this shock captures academic, personal, and family reasons that lead one to not enroll in college, we target conditional enrollment rates in the group least affected by financial constraints. The parameter β_c, the degree of a parent's altruism toward their child, is set so that the model matches average parent-to-child transfers estimated in the NLSY97 (Table A12, Appendix A.1.4). The parameter that determines the labor share for low-education labor, ν, is set so that the college wage premium for the middle skill tercile s_2 matches that observed in the data (Table A10, Appendix A.1.3). Table A21 in Appendix C shows that the resulting college wage premium in the model baseline equilibrium aligns well with its empirical counterpart for all skill terciles.

Panel B of Table 8 contains parameters governed by moments from other sources. The cost of college room and board, $\bar{c}$, is set using the average annual value for room and board, and annual tuition, κ, targets average net tuition and fees; we compute both empirical moments for bachelor's degree programs from 2016-2018 using information from NCES (2019) and the College Board report Ma, Pender, and Libassi (2020). The income exempt from garnishment in delinquency, $\bar{y}$, is set based on our calculations using statutory values reported by Wage and Hour Division, United States Department of Labor (2020). The parameter governing the costs of being delinquent on federal student loans, ξ_D, is set so that the model's per-period delinquency rate matches the average cohort delinquency rate (repayment delayed 270 days or more) from 2016 to 2018 as reported in FSA (2021b). Aggregate labor productivity, Z, is set so that GDP per capita for the population 18 and over is 1 in the model. The discount factor, β, is calibrated to target a capital-to-output ratio consistent with Jones (2016). Finally, the Social Security replacement rate, χ, targets the average ratio of total Social Security expenditure to GDP from 2016 to 2018, estimated using BEA (2022, T2.1) and BEA (2022, T1.1.5).

Table 8: Internally calibrated parameters

Symbol	Parameter description	Parameter value	Moment description	Data moment	Model moment
Panel A: Moments from the NLSY97					
$p(s)$	Continuation prob. average	(0.819,0.877,0.937)	Grad. probability | enr.	*(0.440,0.584,0.771)*	*(0.440,0.584,0.771)*
λ	Net college effort cost	-1.482	Enr. by age 25	*0.501*	*0.501*
$q(s)$	Enrollment option shock	(0.389,0.592,0.891)	Enr. by age 25 | High fam. inc.	*(0.357,0.565,0.878)*	*(0.357,0.565,0.878)*
β_c	Parental altruism toward child	0.183	Ave. transfer, normalized	*0.589*	*0.589*
ν	Low-education labor share	0.440	College wage premium | s_2	*1.380*	*1.380*
Panel B: Moments from other sources					
$\bar{c}$	College room and board	0.147	Room + board, normalized	*0.147*	*0.147*
κ	Annual tuition	0.174	Net tuition + fees, normalized	*0.088*	*0.088*
$\bar{y}$	Garnishment-exempt income	0.140	Exempt earnings, normalized	*0.140*	*0.140*
ξ_D	Federal delinquency cost	0.097	Federal delinquency rate	*0.073*	*0.081*
Z	Aggregate labor productivity	0.540	GDP per capita 18+	*1.000*	*1.000*
β	Discount factor	0.972	Capital-to-output ratio	*3.000*	*3.000*
χ	SS replacement rate	0.188	SS expenditure, fraction of GDP	*0.048*	*0.048*

5 Enrollment Responsiveness, Loan Utilization, and Over-enrollment

In Section 5.1, we perform two validation exercises in the model's initial stationary equilibrium (the "baseline"). Specifically, we compare the model's enrollment responsiveness to subjective beliefs and tuition subsidies with empirical counterparts. In Section 5.2, we report federal student loan utilization rates computed using data from the HSLS:09, and examine the fit of analogous statistics computed in the model baseline equilibrium. Finally, in Section 5.3, we introduce the concept of "over-enrollment" due to subjective beliefs and analyze its effects on enrollment rates by skill.[21]

5.1 Enrollment responsiveness to beliefs and tuition

The first row of Table 9 compares data and model enrollment responsiveness to subjective beliefs in the cross-section (second and third column, respectively), where the "Model" Average Marginal Effect (AME) is computed using a probit estimation like the one in model (2) of Table 2 in Section 2.1. Specifically, this exercise predicts the likelihood of college enrollment using output from the structural model, where the independent variable is reported beliefs in the model "survey," after controlling for the child's skill, parental income, and parental education. Although not targeted in our calibration, the model AME matches the empirical estimate. This result indicates that our model produces a quantitatively reasonable role for subjective beliefs in determining college enrollment choices. Furthermore, this result offers supporting evidence for our mapping of the data on subjective beliefs about the likelihood of BA attainment to the model.

The second row of Table 9 reports enrollment responsiveness to tuition subsidies using the change

[21] In Appendix C, we examine the role of subjective beliefs in generating borrowing behavior in the baseline.

Table 9: Model validation experiments for enrollment responsiveness

Experiment	Data	Model
Average Marginal Effect of subjective beliefs on enrollment likelihood	0.40	0.40
Enrollment change due to additional \$1,000 tuition subsidy	4.00	3.34

Notes: Table 9 reports empirical and model estimates for two model validation experiments. The first row reports the Average Marginal Effect of subjective beliefs on college enrollment likelihood from a probit model. The data estimate is from model (2) of Table 2 in Section 2.1; the model estimate is from a probit estimation on model output in which the dependent variable is the enrollment decision and the independent variable is the reported belief as well as individual and family characteristics (i.e., child skill, logged parental income, and parental education). The second row reports changes in the enrollment rate given a \$1,000 tuition subsidy increase, where the data moment is reported by Deming and Dynarski (2009) and model moment is constructed in partial equilibrium. All units are in percentage points.

in the enrollment rate for an additional \$1,000 tuition subsidy (i.e., a quasi-experiment), in the data and in the model in partial equilibrium. The data estimate is from Deming and Dynarski (2009), who survey the literature on empirical estimates for enrollment responses to tuition subsidies, and conclude that the best estimates suggest a value of 4 percentage points. The model does well in matching this untargeted moment, with a response of 3.34 percentage points. This result suggests that our model produces a quantitatively reasonable role for college costs in determining college enrollment decisions.

5.2 Federal student loan utilization rates

Consistent with recent federal student loan policy, the baseline's federal student loan limit is enough to pay for 37.3 percent of annual average total college costs. To what extent are college students using the federal loans to which they have access in the data, and how does the model perform in matching utilization rates? To measure utilization rates in the data, we turn

Table 10: Utilization rates for federal student loans

Utilization	Data	Model
$\geq 50\%$	54	50
$\geq 90\ \%$	34	15
$\geq 100\%$	28	9
Obs	1,855	

Notes: Table 10 reports utilization rates for federal student loans in the data and in the baseline model equilibrium. Data moments are estimated for students who enrolled in a BA program in the fall of 2013 and persisted to the end of their third academic year. For data and model moments, utilization rates of federal student loans are computed as percentages of the cumulative limit up to that point (the sum of annual limits for the first three academic years). Data moments use PETS-SR student records longitudinal weights. Data source: HSLS:09.

to the HSLS:09.[22] We compute the federal loan utilization rate for college enrollees who persist for three academic years after enrollment, where the utilization rate is the ratio of the cumulative federal debt balance to cumulative borrowing limits after the first three years of college. Table 10 reports the results: 54 percent of those who completed their third academic year utilized more than half of their cumulative federal student loan limit, 34 percent utilized more than 90 percent, and 28 percent utilized all of their available federal loans at the end of their third academic year. Although these moments are not targeted in the calibration, Table 10 indicates that the model's baseline equilibrium does well in matching the share of college enrollees with a utilization rate of 50 percent or higher. The model understates the share of students using all of their available federal loans. Because we underestimate this share in the model baseline, our welfare estimates from loan expansions can be considered lower bounds.

5.3 Over-enrollment

Column (1) of Table 11 reports enrollment rates for each skill tercile in the NLSY97, drawn from Table A4 of Appendix A.1, while column (2) reports enrollment rates in the model's calibrated baseline. Moments from the model align reasonably well with the data. Column (3) of Table 11 reports enrollment rates after netting out over-enrollment for the same distribution of high school graduates as column (2). An enrollee is counted as "over-enrolled" if they enroll with subjective beliefs but would not with correct beliefs. This counterfactual calculation is performed in a partial equilibrium in which we shut off subjective beliefs by setting $\hat{p} = p(s)$ for all s but do not allow general equilibrium objects to adjust. Without over-enrollment, enrollment rates decrease especially among low- and medium-skill 18-year-olds. Columns (4) and (5) of Table 11 report the mass of 18-year-olds who are over-enrolled as a share of high school graduates and as a share of enrollees, respectively. Over-enrollment both as a share of high school graduates and as a share of enrollees is highest among the low skill. Furthermore, the difference between over-enrollment as a share of high school graduates and as a share of enrollees is particularly large for those with low skill. The reason for this pattern is that the calibrated values for the skill-specific enrollment shock, $q(s)$, are increasing in skill. Therefore, for the 18-year-olds with low skill, this shock acts to dampen over-enrollment.

[22]To apply for federal aid, college students submit the Free Application for Federal Student Aid (FAFSA). Students select a dependency status on the FAFSA, which determines annual borrowing limits for federal student loans. The public version of the HSLS:09 does not report which dependency status each FAFSA filer selects. We assume everyone files as dependents because most undergraduate students (and all students in the HSLS:09 in 2016, the year in which we measure their utilization rates) are less than 24 years old. Besides age, other ways to be classified as independent are to be married, enroll in a graduate program, serve on active duty in the U.S. armed forces or be a veteran, have dependent children, have deceased parents, be an emancipated minor, or be determined as an unaccompanied minor (FSA, 2022b). Most undergraduate students do not satisfy these criteria.

Table 11: College enrollment statistics by skill

Statistic:	**College enrollment rates**			**Over-enrollment**	
Sample:	**High school graduates**			**High school graduates**	**College enrollees**
Skill	**(1) Data**	**(2) Baseline**	**(3) Baseline, no over-enrollment**	**(4) Baseline**	**(5) Baseline**
Low	22.92	24.31	20.96	3.36	13.80
Medium	50.29	45.74	43.08	2.66	5.82
High	76.70	80.24	79.75	0.48	0.60

Notes: Table 11 presents enrollment statistics in the data and model by skill, where skill bin is assigned with ASVAB tercile in the data and represented with s in the model. Enrollment rates are computed after high school graduation as percentages of the skill bin who enroll in a BA program. Columns (1), (2), and (3) report the enrollment rates in the data, in the initial stationary equilibrium of the model, and in the initial stationary equilibrium of the model excluding over-enrollment; columns (4) and (5) report over-enrollment as a share of high school graduates and enrollees, respectively. The definition of over-enrollment is provided in the main text. All units are in percentages. Data source: NLSY97.

6 Main Experiment: Federal Loan Limit Expansion

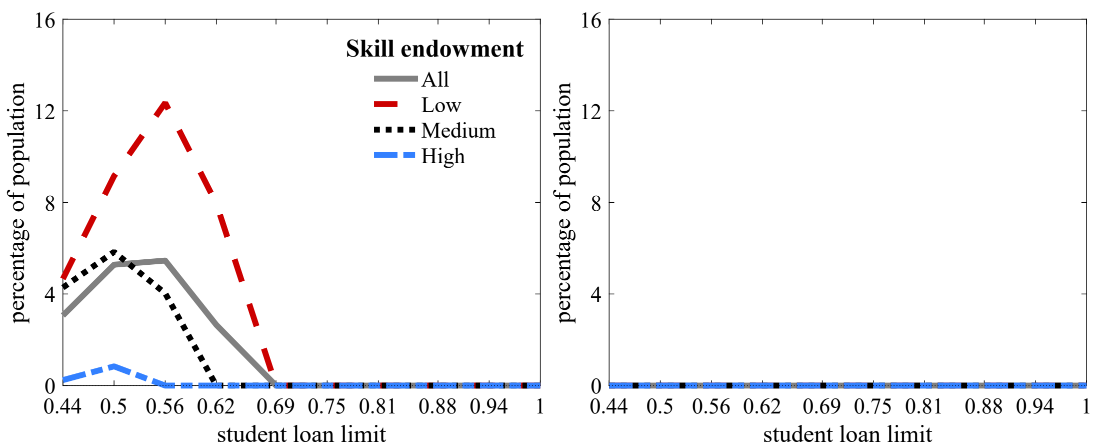
The high utilization rates we find in both the data and the model, along with our model results on optimistic subjective beliefs leading to over-enrollment—both presented in Section 5—motivate us to analyze the welfare impact of access to student loans. This section analyzes the welfare effects of expanding the federal student loan limit, $\bar{A}$, whereas in Appendix E we analyze a limit contraction.

The welfare consequences of a federal student loan limit expansion are ex-ante ambiguous: access to more federal credit potentially worsens over-enrollment for optimistic high school graduates while also relaxing a binding constraint. The parameterized model determines the relative magnitude of each of these forces. To highlight the role of subjective beliefs, for illustrative purposes our analysis also includes results from a limit expansion in an economy without subjective beliefs that is re-calibrated to match the same set of target moments as the baseline. Specifically, in Section 6.1 we show how some 18-year-olds are made worse off because of a limit expansion in our framework in partial equilibrium via comparative statics. Subsequently, Section 6.2 provides an in-depth analysis of welfare changes from a specific limit expansion in partial equilibrium in which the highest share of 18-year-olds are made worse off. Finally, Section 6.3 analyzes the effects of general equilibrium adjustments on the limit expansion analyzed in Section 6.2.

Welfare To measure welfare, we assume that the social planner takes consumer decisions as given but internalizes that the consumer has subjective beliefs when making the college enrollment decision, the inter vivos transfer decision, and the decisions leading up to and including the age at which the inter vivos transfer is made (i.e., the planner uses the correct probabilities for the likelihood of continuing in college). We compute welfare for 18-year-old consumers before the realization of the college enrollment option shock; this age group is the one most affected by the policy change. We report two welfare statistics: first, the population share that is strictly worse or better off, calculated by comparing the lifetime values as computed by the social planner; and, second, consumption-equivalent variation, calculated as explained in Appendix B.4.

6.1 How a limit expansion hurts 18-year-olds in partial equilibrium

Figure 3 highlights the key result of this paper via comparative statics from a limit expansion: in partial equilibrium, a limit expansion can make 18-year-olds worse off, especially those with low skill. For example, when the limit expands from the status quo of $\bar{A} = 0.37$ to $\bar{A} = 0.56$, Figure 3a shows that approximately 5 percent of all 18-year-olds are worse off. Furthermore, although some 18-year-olds are worse off for a moderate limit expansion, $\bar{A} \in [0.44, 0.69)$, no one is worse off for a sufficiently large limit expansion, $\bar{A} \in [0.69, 1]$. However, in a re-calibrated model without subjective beliefs, no one is strictly worse off for any level of a limit expansion as illustrated by Figure 3b. The distribution of subjective beliefs, which is a feature of the data that we use to inform our model, drives the result that 18-year-olds can be worse off from a limit expansion.



(a) Baseline

(b) No subjective beliefs

Figure 3: Share of 18-year-olds strictly worse off

Notes: Figures 3a and 3b plot the share of 18-year-olds that are strictly worse off, overall and for each skill endowment, after a federal loan limit expansion in our model with subjective beliefs ("Baseline") and in an alternative re-calibrated framework without subjective beliefs ("No subjective beliefs"), respectively. The analyses presented in these figures are from a partial equilibrium exercise in which the income tax rate, prices, bequests, Social Security transfers, and the 18-year-old distribution are fixed at their initial steady state values. On the x-axes, the student loan limit ($\bar{A}$) refers to the limit in the new equilibrium, where $\bar{A} = 1$ implies that the annual federal loan limit is equal to the annual college tuition and fees, net of grants, plus room and board. The share of the population that is strictly better off is the reciprocal of those that suffer losses (that is, no 18-year-old is indifferent).

We discuss why welfare losses arise in partial equilibrium for a moderate limit expansion before discussing why welfare losses do not arise for a large limit expansion. For a moderate limit expansion, welfare losses arise because the limit expansion increases over-enrollment: young people who did not enroll in the baseline now would do so given the option to enroll entirely because of their optimistic beliefs. In Appendix D.1, we show that, if we shut off parental altruism, transitioning from being a non-enrollee to being an over-enrolled college student after the loan limit expansion is both sufficient and necessary to suffer welfare losses. With altruism, we establish that this equivalence is quantitatively the main driver of partial-equilibrium welfare losses in our calibrated baseline model with subjective beliefs. Specifically, Table 12 reports statistics to establish equivalence between those strictly worse off and those would who flow from from non-enrollment to over-enrollment given the option to enroll at three limit expansions in the baseline model. Among those who are strictly worse off after each limit expansion, 100 percent flow from non-enrollment to over-enrollment; among those who flow from non-enrollment to over-enrollment, 100 (or close to 100) percent are strictly worse off.

Table 12: Equivalence of worse off and inflow from non-enrollment to over-enrollment

$\bar{\mathrm{A}}_{\text{initial}}$ to $\bar{\mathrm{A}} = \ldots$	Inflow from non-enrollment to over-enrollment | Worse off	Worse off | Inflow from non-enrollment to over-enrollment
0.44	100	100
0.50	100	100
0.56	100	98

Notes: Table 12 reports the share who flow from non-enrollment to over-enrollment among the 18-year-olds who are strictly worse off, as well as the share who are strictly worse off among 18-year-olds who flow from non-enrollment to over-enrollment. These results are from a partial equilibrium exercise in which the income tax rate, prices, bequests, Social Security transfers, and the 18-year-old distribution are fixed at their initial steady state values.

While welfare losses arise for a moderate limit expansion, they do not for a sufficiently large limit expansion as illustrated by Figure 3a. This is because flows from non-enrollment to over-enrollment are observed for a moderate limit expansion, but not for a sufficiently large limit expansion. This model outcome is illustrated in Figure 4. The reason for the lack of over-enrollment for a large limit expansion is a continued rise in the ability to smooth consumption during the college phase, which leads to a rise in the value of college such that consumers are no longer over-enrolled. As supporting evidence for this intuition, in Table A25 of Appendix D.2 we show how, at a sufficiently large loan limit expansion, the realized value of college increases so that consumers are no longer over-enrolled.

As for attributing this rise in the value of college to consumption-smoothing benefits in particular, Figure 5 illustrates the increased ability to smooth consumption after a large limit expansion compared to a moderate one. For the purpose of this illustration, we identify a specific group and then plot their consumption by age in two limit expansion scenarios in partial equilibrium. Consequently, the only factor that can lead to changes in consumption across the two scenarios is

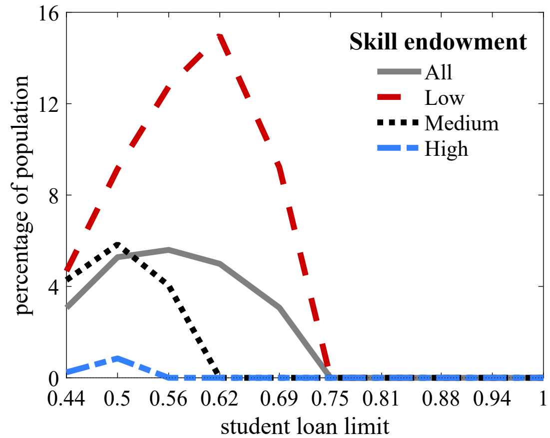


Figure 4: Inflow from non-enrollment to over-enrollment | Option to enroll

Notes: Figure 4 plots the share of 18-year-olds who, given the option to enroll in college, would flow from non-enrollment in the initial stationary equilibrium to over-enrollment after a federal loan limit expansion, overall and for each skill endowment, in the baseline model with subjective beliefs. The analyses presented in this figure are from a partial equilibrium exercise in which the income tax rate, prices, bequests, Social Security transfers, and the 18-year-old distribution are fixed at their initial steady state values. The x-axis is the annual student loan limit $(\bar{A})$ in the new equilibrium, where $\bar{A} = 1$ implies that the annual federal loan limit is equal to the annual college tuition and fees, net of grants, plus room and board.

the limit change. The specific group is identified as 18-year-olds who, given the option to enroll, would go from non-enrollment in the initial stationary equilibrium to over-enrollment when the limit expands to $\bar{A} = 0.56$. The two limit expansions we compare are $\bar{A} = 0.56$ and $\bar{A} = 1$. For the same population of 18-year-olds, the figure shows that, in comparison to a moderate limit expansion ($\bar{A} = 0.56$, dashed red line), a large limit expansion ($\bar{A} = 1$, dashed-dotted blue line) leads to higher consumption at ages 18, 19, 20, and 21 (i.e., the college phase).

6.2 Welfare changes in partial equilibrium

In the previous section, we showed that a moderate expansion in limits could make some 18-year-olds worse off because they may respond by transitioning from non-enrollment to over-enrollment. In this section, we provide an in-depth analysis of welfare changes of a moderate limit expansion in partial equilibrium. We report welfare changes when the limit expands to $\bar{A} = 0.56$, the limit at which the most 18-year-olds are worse off in partial equilibrium.

In the first two columns of Table 13, we quantify the magnitudes of welfare changes in partial equilibrium. Within each skill endowment this table reports the shares worse off and better off and, by skill and sign of welfare change, the magnitude of the welfare change for the average 18-year-old in that category and the conditional mean of initial characteristics: assets, AR(1) earnings productivity, and beliefs. In partial equilibrium, for those strictly worse off (who are only in the

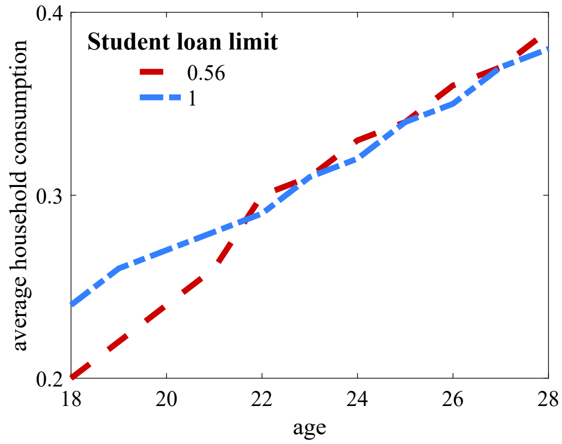


Figure 5: Consumption by age

Notes: Figure 5 plots the average consumption by age for a specifically identified group of consumers under two limit expansion counterfactuals. The specifically identified group includes 18-year-olds who, given the option to enroll, would go from non-enrollment in the initial stationary equilibrium to over-enrollment when the limit expands to $\bar{A} = 0.56$. The two limit expansion counterfacturals are $\bar{A} = 0.56$ and $\bar{A} = 1$. The analyses presented in this figure are from a partial equilibrium exercise in which the income tax rate, prices, bequests, Social Security transfers, and the 18-year-old distribution are fixed at their initial steady state values. The x-axis is age.

low and medium skill bins) the average welfare losses amount to roughly 0.7 and 0.2 percent of lifetime consumption, respectively. In addition to having lower skill, those worse off tend to have low initial assets, low initial AR(1) productivity, and high expectations about the likelihood of BA in comparison to those who are better off. Furthermore, as shown in the first row of Table 14, although restricted to the low and medium skill, those who are worse off are not a small group: they account for 5 percent of all 18-year-olds. Therefore, the number of 18-year-olds who experience welfare losses and the magnitudes of the welfare losses are sizable. Among those strictly better off, the largest welfare gains are experienced by 18-year-olds with high skill. Additionally, in Appendix D.3.1, we show that these 18-year-olds with high skill are from poor families, tend to have a low initial AR(1) productivity, and have moderate to high expectations about their own likelihood of earning a BA.

6.3 Welfare changes in general equilibrium

General equilibrium adjustments act to dampen the increase in the value of college from a limit expansion and increase the value of not going to college. Table A27 of Appendix D.3.2 reports details on the resulting changes to education and skill statistics, macroeconomic aggregates, and general equilibrium objects. In particular, the wage rate and Social Security transfers for a low-education worker increase, whereas they decrease for a high-education worker; the risk-free rate interest rate on savings increases slightly, which increases the interest rate for federal student loans;

Table 13: Characteristics of the strictly worse off and strictly better off ($\bar{A}_{\text{initial}}$ to $\bar{A} = 0.56$)

		Partial equilibrium		General equilibrium	
Skill	**Variable**	**Worse off**	**Better off**	**Worse off**	**Better off**
Low	Share (unit: percentage)	12.35	87.65	3.80	96.20
	Consumption-equivalent variation (unit: percentage points)	-0.73	0.29	-0.16	1.12
	Average assets (unit: numeraire)	0.00	0.70	0.02	0.60
	Average η (unit: labor efficiency)	0.75	1.23	0.58	1.20
	Average belief (unit: percentage)	91.00	66.00	95.00	69.00
Medium	Share	4.03	95.97	0.00	100.00
	Consumption-equivalent variation	-0.20	0.79	-2.97†	1.47
	Average assets	0.00	0.59	0.91†	0.50
	Average η	0.47	1.20	1.08†	1.17
	Average belief	89.00	78.00	18.00†	78.00
High	Share	0.00	100.00	20.14	79.86
	Consumption-equivalent variation	n/a	1.87	-0.23	2.85
	Average assets	n/a	0.60	1.64	0.22
	Average η	n/a	1.17	1.22	1.16
	Average belief	n/a	88.00	88.00	88.00

Notes: Table 13 groups 18-year-olds who are strictly worse off and strictly better off when the limit expands from $\bar{A}_{\text{initial}}$ to $\bar{A} = 0.56$ in the baseline model and reports the following statistics by skill endowment: shares strictly worse/better off, consumption-equivalent variation, and conditional means of characteristics such as assets, AR(1) productivity, and expectations about BA likelihood. "Partial equilibrium" refers to a partial equilibrium exercise in which the income tax rate, prices, bequests, Social Security transfers, and the 18-year-old distribution are fixed at their initial steady state values. For the comparison in general equilibrium, the final steady state distribution of 18-year-olds was used. "n/a" refers to cases in which no one is strictly worse off (or better off) in a given cell; "$\dagger$" refers to cases in which almost no one is strictly worse off (or better off), but the share is not exactly 0 in a given cell.

the income tax rate decreases slightly; parental transfers for college decrease; and accidental bequests increase. We next examine how the welfare impact of the limit expansion analyzed in the previous section is affected by these general-equilibrium adjustments. We follow the same order as our partial-equilibrium analysis of Section 6.2 by first discussing changes in the share worse off by skill tercile (Table 14) and then analyzing the magnitude of welfare changes in general equilibrium (last two columns of Table 13).

The second row of Table 14 reports the share of 18-year-olds that are strictly worse off after a moderate limit expansion in general equilibrium, both overall and for each skill endowment. As with the partial equilibrium analysis, we contrast this statistic for our model with subjective beliefs to one computed in a re-calibrated model without subjective beliefs. In the baseline general equilibrium economy, fewer 18-year-olds with low and medium skill are strictly worse off in comparison to the partial equilibrium case. This is because the value of a low-education worker (which is the more likely outcome for an 18-year-old with lower skill) increases relative to the initial equilibrium due to a rise in the wage rate for that education type. Consequently, although over-enrollment increases among those with low and medium skill (see Table A27), the welfare cost of the rise in over-enrollment is dampened by the rise in the low-education wage rate.

Table 14: Share of 18-year-olds strictly worse off ($\bar{A}_{\text{initial}}$ to $\bar{A} = 0.56$)

	Baseline				No subjective beliefs			
		Skill				Skill		
Equilibrium	**All**	**Low**	**Medium**	**High**	**All**	**Low**	**Medium**	**High**
Partial	5	12	4	0	0	0	0	0
General	8	4	0	20	7	0	0	21

Notes: Table 14 reports the share of 18-year-olds that are strictly worse off, overall and for each skill endowment, after a federal loan limit expansion from $\bar{A}_{\text{initial}} = 0.37$ to $\bar{A} = 0.56$ in our model with subjective beliefs ("Baseline" columns) and in an alternative re-calibrated framework without subjective beliefs ("No subjective beliefs" columns). Rows determine the equilibrium concept being applied: "Partial" refers to a partial equilibrium exercise in which the income tax rate, prices, bequests, Social Security transfers, and the 18-year-old distribution are fixed at their initial steady state values; "General" refers to general equilibrium. For the welfare comparison in general equilibrium, the final steady state distribution of 18-year-olds was used. The share of the population that is strictly better off is the reciprocal of those that suffer losses (that is, no 18-year-old is indifferent).

At the same time, Table 14 also shows that a fifth of those with high skill are worse off in general equilibrium, whereas no one with high skill was worse off in partial equilibrium. A rise in the share of the high-skilled who suffer welfare losses in general equilibrium is also seen in the framework with correct beliefs. The common pattern across the two model environments is due to a decrease in the value of a high-education worker (which is the most likely outcome for an 18-year-old with high skill) relative to the initial equilibrium due to a fall in the wage rate for that education type. In Appendix D.3.3 we show that, among general equilibrium objects, the rise in the wage rate for the low-education worker is the primary driver of losses dampening for consumers with lower skill and the fall in the wage rate for high-education workers is the primary driver of welfare losses arising for the consumers with the highest skill.

Returning to Table 13, the last two columns report changes in welfare and conditional means of initial characteristics across steady states in general equilibrium. In comparison to the partial equilibrium counterparts in the same table, the magnitudes of welfare losses for the the low-skill are dampened. For example, among the low-skill who are worse off, the welfare losses in general equilibrium amount to 0.16 percent of lifetime consumption, whereas the partial equilibrium estimate is 0.73 percent of lifetime consumption.[23] In Appendix D.3.4, we analyze welfare changes along the transition path. We show that general equilibrium effects dampen welfare losses, but take some time to materialize.

Finally, to highlight the role of subjective beliefs in a limit expansion for the average high school graduate, in Table 15 we compare welfare changes in general equilibrium with subjective beliefs to welfare changes in an environment with correct beliefs for the average 18-year-old. The table

[23] Among those with medium skill, almost no one experiences welfare losses in general equilibrium, and therefore the consumption-equivalent variation estimate is irrelevant.

leads to the following takeaway: even with subjective beliefs, the average 18-year-old is better off from the limit expansion, but the gains are smaller in comparison to the environment with correct beliefs.[24]

Table 15: Consumption-equivalent variation for average 18-year-old ($\bar{A}_{\text{initial}}$ to $\bar{A} = 0.56$)

General equilibrium		
Baseline	**No subjective beliefs**	**Difference**
0.94	1.34	0.40

Notes: Table 15 reports consumption-equivalent variation estimates in units of percentage points in the baseline economy ("Baseline" columns) and in a re-calibrated economy without subjective beliefs ("No subjective beliefs" columns) when there is an expansion in the limit from $\bar{A}_{\text{initial}}$ to $\bar{A} = 0.56$ for the average 18-year-old. To compute welfare, we compare the average initial steady state value to the corresponding average final steady state value.

In summary, our results show that, with optimism about the likelihood of college graduation, a moderate limit expansion can make some low- and medium-skill 18-year-olds worse off. Furthermore, for those worse off, the magnitudes of the welfare losses are sizable. More generally, we view our main experiment as one that highlights how access to student loans can hurt some 18-year-olds in the presence of widespread optimism. In the main experiment, the mechanism by which 18-year-olds are hurt is a transition from non-enrollment to over-enrollment. These results rely on the difference between the expected and true likelihood of continuing in college among non-enrollees, where the true likelihood of continuing was imputed using probabilities of enrollees in the same skill tercile as described in Section 4. In Appendix E, we show that access to student loans can hurt some 18-year-olds by analyzing a *contraction* in the student loan limit. For this experiment, the beliefs and the true likelihood of continuing in college for non-enrollees do not matter as much because gains due to the limit contraction are experienced by college enrollees who are over-enrolled in the initial equilibrium, but transition to non-enrollment when the limit contracts.

7 Conclusion

In this paper, we document empirically that both young adults and their parents exhibit subjective beliefs about the likelihood of earning a bachelor's degree that positively predict college enrollment and that are often optimistic. We build a structural model of college choice that features these subjective beliefs along with key sources of college financing, and use it to examine the welfare effects of access to federal student loans. We find that access to student loans can lead to welfare

[24] In the presence of subjective beliefs, the average consumer alive in the first period of the transition also benefits: the welfare gains amount to 0.30 percent.

losses for low-skill young adults who are poor and exhibit a high degree of optimism. This happens because these young adults transition from non-enrollment to over-enrollment (that is, enrollment due to optimistic beliefs). We hope that the empirical findings and quantitative analysis presented here will be useful for researchers seeking to evaluate and improve the design of college financial aid.

References

109th Congress of the United States of America (2006). Deficit Reducation Act of 2005 (Public Law 109-171). (accessed 05.10.2024).

Abbott, B., G. Gallipoli, C. Meghir, and G. Violante (2019). Education Policy and Intergenerational Transfers in Equilibrium. *Journal of Political Economy 127*(6).

Andolfatto, D. and M. Gervais (2006). Human capital investments and debt constraints. *Review of Economic Dynamics 2*, 52–67.

Barber, B. M. and T. Odean (2001). Boys will be boys: gender, overconfidence, and common stock investment. *Quarterly Journal of Economics 116*(1), 261–292.

Bell, F. C. and M. L. Miller (2020). Life Tables for the United States Social Security Area, 1900-2100, Actuarial Study No. 6, Table 6. (accessed 06.01.2022).

Bureau of Economic Analysis, U.S. Department of Commerce (2022a). Table 2.1. (accessed 05.15.2022).

Bureau of Economic Analysis, U.S. Department of Commerce (2022b). Table 1.1.5. (accessed 05.15.2022).

Bureau of Economic Analysis, U.S. Department of Commerce (2022c). Table 3.1. (accessed 05.15.2022).

Bureau of Labor Statistics, U.S. Department of Labor (2012a). Parent Questionnaire 97 (R1). (accessed 05.26.2024).

Bureau of Labor Statistics, U.S. Department of Labor (2012b). Youth Questionnaire 97 (R1). (accessed 05.26.2024).

Bureau of Labor Statistics, U.S. Department of Labor (2019). National Longitudinal Survey of Youth 1997 cohort, 1997-2019 (rounds 1-19). Produced and distributed by the Center for Human Resource Research (CHRR), The Ohio State University. Columbus, OH.

Bureau of Labor Statistics, U.S. Department of Labor (2021). Consumer Price Index for All Urban Consumers: All Items in U.S. City Average [CPIAUCSL]. Retrieved from FRED, Federal Reserve Bank of St. Louis. (accessed 05.23.2024).

Bureau of Labor Statistics, U.S. Department of Labor (2024). Appendix 10: CAT-ASVAB Scores. (accessed 04.27.2024).

Card, D. and T. Lemieux (2001). Can falling supply explain the rising return to college for younger men? A cohort-based analysis. *The Quarterly Journal of Economics 116*(2), 705–746.

Caucutt, E. and L. Lochner (2020). Early and Late Human Capital Investments, Borrowing Constraints, and the Family. *Journal of Political Economy 128*(3), 1065–1147.

Caucutt, E. M. and K. B. Kumar (2003). Higher education subsidies and heterogeneity: a dynamic analysis. *Journal of Economic Dynamics and Control 27*(3), 1459–1502.

Census Bureau of the United States (2020). National Population by Characteristics: 2010-2019. Produced by the Census Bureau of the United States. (accessed 05.23.2024).

Chatterjee, S. and F. Ionescu (2012). Insuring student loans against the financial risk of failing to complete college. *Quantitative Economics 3*, 393–420.

Chetty, R. (2006). A New Method of Estimating Risk Aversion. *The American Economic Review 96*(5), 1821–1834.

Chief Operating Officer for Federal Student Aid (2021). Annual Notice of Interest Rates for Fixed-Rate Federal Student Loans Made Under the William D. Ford Federal Direct Loan Program. *Federal Register 86*(152), 44003–44005. (accessed 07.05.2022).

Colas, M., S. Findeisen, and D. Sachs (2021). Optimal need-based financial aid. *Journal of Political Economy 129*(2), 492–533.

Deming, D. and S. Dynarski (2009). Into college, out of poverty? Policies to increase the postsecondary attainment of the poor. *NBER Working Paper 15387*.

Duprey, M., D. Pratt, D. Jewell, D. Brown, L. . Caves, S. Kinney, T. Mattox, M. Smith Ritchie, J. Rogers, C. Spagnardi, and J. Wescott (2020). High School Longitudinal Study of 2009 (HSLS:09) Postsecondary Education Transcript Study and Student Financial Aid Records Collection. (accessed 05.02.2022).

Exler, F., I. Livshits, J. MacGee, and M. Tertilt (2021). Consumer credit with over-optimistic borrowers. *Unpublished manuscript*.

Goldin, C. and L. F. Katz (2007). The race between education and technology: The evolution of U.S. educational wage differentials, 1890 to 2005. *NBER Working Paper 12984*.

Hagenaars, A. J., K. de Vos, and M. A. Zaidi (1994). Poverty Statistics in the Late 1980s: Research based on micro-data. *Eurostat report*.

Heathcote, J., K. Storesletten, and G. L. Violante (2017). Optimal Tax Progressivity: An Analytical Framework. *Quarterly Journal of Economics 132*, 1693–1754.

Ionescu, F. (2009). The Federal Student Loan Program: Quantitative Implications for College Enrollment and Default Rates. *Review of Economic Dynamics 12(1)*, 205–231.

Ionescu, F. and N. Simpson (2016). Default Risk and Private Student Loans: Implications for Higher Education Policies. *Journal of Economic Dynamics and Control 64*, 119–147.

Jones, C. (2016). Facts About Economic Growth. *Handbook of Macroeconomics 2A*.

Krueger, D. and A. Ludwig (2016). On the optimal provision of social insurance: Progressive taxation versus education subsidies in general equilibrium. *Journal of Monetary Economics 77*, 72–98.

Krumpal, I. (2013). Determinants of social desirability bias in sensitive surveys: a literature review. *Quality & Quantity 47*, 2025–2047.

Kydland, F. E. and E. C. Prescott (1982). Time to Build and Aggregate Fluctuations. *Econometrica 50(6)*, 1345–1370.

Lochner, L. J. and A. Monge-Naranjo (2011). The Nature of Credit Constraints and Human Capital. *The American Economic Review*, 2487–2529.

Luo, M. and S. Mongey (2019). Assets and job choice: Student debt, wages and amenities. *Unpublished manuscript*.

Ma, J., M. Pender, and C. Libassi (2020). Trends in College Pricing and Student Aid 2020. *College Board*.

Matsuda, K. (2020). Optimal timing of college subsidies: Enrollment, graduation, and the skill premium. *European Economic Review 129*, 103549.

Matsuda, K. (2022). Progressive Taxation versus College Subsidies with College Dropout. *Journal of Money, Credit and Banking* (available online).

Mendoza, E. G., A. Razin, and L. L. Tesar (1994). Effective tax rates in macroeconomics: Cross-country estimates of tax rates on factor incomes and consumption. *Journal of Monetary Economics 34*, 297–323.

Moschini, E. G., G. Raveendranathan, and M. Xu (2023). Optimism About Graduation and College Financial Aid. *Unpublished manuscript*.

Nakajima, M. (2012). Rising indebtedness and temptation: A welfare analysis. *Quantitative Economics 3(2)*, 257–288.

Nakajima, M. (2017). Assessing bankruptcy reform in a model with temptation and equilibrium default. *Journal of Public Economics 145*, 42–64.

National Center for Education Statistics, U.S. Department of Education (2019). Table 330.10. Produced and distributed by the Institute of Education Sciences, National Center for Education Statistics (NCES). (accessed 01.04.2022).

National Center for Education Statistics, U.S. Department of Education (2020a). High School Longitudinal Study of 2009 (public use data file). Produced and distributed by the Institute of Education Sciences, National Center for Education Statistics (NCES). (accessed 10.11.2022).

National Center for Education Statistics, U.S. Department of Education (2020b). Table 331.35. Produced and distributed by the Institute of Education Sciences, National Center for Education Statistics (NCES) (accessed 01.04.2022).

OECD (2024a). Annual government expenditure by function (COFOG). Public use dataset, OECD.

OECD (2024b). Annual household final consumption expenditure on the territory and abroad. Public use dataset, OECD.

OECD (2024c). Details of Tax Revenue - United States. Public use dataset, OECD.

Office of Federal Student Aid, U.S. Department of Education (2022). Dependency Status. (accessed 12.01.2022).

Smole, D. P. (2019). Federal Student Loans Made Through the William D. Ford Federal Direct Loan Program: Terms and Conditions for Borrowers. (Congressional Research Service of the United States R45931).

Stinebrickner, T. and R. Stinebrickner (2012). Learning about academic ability and the college dropout decision. *Journal of Labor Economics 30(4)*, 707–748.

Survey Research Center, Institute for Social Research (2021). Panel Study of Income Dynamics. Public use dataset, University of Michigan, Ann Arbor , MI.

U.S. Congressional Budget Office (2019). The Distribution of Household Income, 2016.

U.S. Congressional Budget Office (2020). The Distribution of Household Income, 2017.

U.S. Congressional Budget Office (2021). The Distribution of Household Income, 2018.

U.S. Department of Education, Office of Federal Student Aid (2021). National Default Rate Briefing for FY 2018 Official Cohort Default Rates. (accessed 05.15.2022).

Wage and Hour Division, United States Department of Labor (2020). Fact Sheet #30: The Federal Wage Garnishment Law, Consumer Credit Protection Act's Title III (CCPA). (accessed 05.11.2024).

Online Appendix for: "Optimism About Graduation and College Financial Aid"
by Emily G. Moschini, Gajendran Raveendranathan, and Ming Xu

Contents

A Data Appendix

A.1 The 1997 National Longitudinal Survey of Youth

The 1997 National Longitudinal Survey of Youth, referred to as the NLSY97, is a nationally representative sample of people born between 1980 and 1984 who lived in the United States in 1997 (Bureau of Labor Statistics, U.S. Department of Labor, 2019). This survey collected data annually from 1997 to 2011 and biannually from 2011 to the present. We use data through 2019 (rounds 1 to 19). There are 8,984 individuals in the raw data. In our estimations, we report real dollar values after converting to 2016 USD using the Consumer Price Index or CPI (BLS, 2021).

A.1.1 Estimation samples

We use the NLSY97 for several sets of results, which share a baseline data cleaning procedure but differ in the additional requirements they make of the data. In particular, we generate the cleaned NLSY97 sample by requiring that we observe the ASVAB percentile score and that, at some point before the sample member turns 30, we see evidence that they are a high school graduate (or, in the portion of the sample when data is collected every 2 years, before they are 30 or 31). Using this "cleaned" sample, which contains 5,868 individuals, we assign the skill tercile that the individual belongs to using the ASVAB percentile score. We also assign observations to a parental income tercile using values of real gross parental income in 1997 for the subset of 4,495 individuals where that variable is nonmissing. Because the demands of each group of exercises in this appendix differ, and conditional sample sizes can become quite low if we require a consistent sample across exercises, we instead start from the cleaned sample and further condition the sample used for each exercise on the requirements of that exercise alone, rather than generating a single sample that we use for every tabulation.

To estimate the tabulations in Section 2 of the main text and Appendix A.1.2, we make three requirements of the cleaned sample. First, a valid sample member response to the educational attainment expectations question must be collected at least once when the respondent is in high school. Note that, in 1997, the educational attainment expectations question is asked of those born in 1980 or 1981, while in 2001, respondents were randomly assigned to one of 4 groups, and 2 of these groups are asked the educational attainment expectations question without conditioning on their age. Second, we must observe the educational attainment of the respondent when they are 30 years old (or, in the portion of the sample when data is collected every 2 years, when they are 30 or 31). Third, we drop individuals for whom the educational attainment variable reports "some college" by age 30, and who were observed in every year of the survey until that age, but for whom there is no indication from previous years about whether they enrolled in a 4-year or a 2-year post-secondary program. This results in a sample of individuals who graduated from high school by age 30 which contains 2,222 individuals, of which 1,200 individuals enroll in a BA by age 30. The sample size is further reduced for tabulations that use variables recording family attributes of the respondent such as parent beliefs or parental income. Additionally, for Panel B of Table 3, we require that beliefs be observed twice and that the respondent have a particular education situation when responding to the question each time: first, in 1997, the response must be collected when the youth is still in high school; and second, in 2001, the respondent must have reported being enrolled in a 4-year program in 1998, 1999, or 2000. This sample contains 234 individuals.

To estimate skill loadings for the life-cycle earnings profile as described in Appendix A.1.3, we make four requirements of the cleaned sample. These requirements are a modified version of those imposed in Abbott, Gallipoli, Meghir, and Violante (2019), adjusted to align with the heterogeneity we include in our model environment. First, we keep the variable recording the individual's tercile of ASVAB percentile score (our measure of skill), as well as respondent age, marital status, educational attainment status, and wage in each wave of the survey. We then reshape the data from individual-level to be a panel at the individual-year level. We convert wages to real values and drop observations with real wages in dollar units above 400 and below 1. Second, we compute wage growth, and drop individual-year observations where annualized wage growth across survey rounds is above 4 percent or below -2 percent. Third, we drop individual-year observations for those enrolled in any education program in that year of the survey. Fourth, we restrict the sample to observations where the respondent is aged between 24 and 39 and skill, age, marital status, education, and wage are all nonmissing. We then group observations of these working individuals as either "high school" meaning those with a high school degree or some college, or "BA" meaning those with a BA degree or more. The resulting panel data, which we use for our estimation of the factor loadings on skill by education category (high school or BA), contains 16,360 individual-year observations for the high school group (3,113 individuals) and 9,406 individual-year observations for the BA group (1,811 individuals).

To estimate average inter vivos transfers from parents to their college-aged children in the NLSY97 as decribed in Appendix A.1.4, we use the sample from the earnings process estimation described in the previous paragraph, but with four modifications involving requirements on respondent age, education status, independence status, and whether the observation has been assigned a parental (family) income tercile. First, we allow individuals to be enrolled in an education program in a given year; second, we restrict attention to individuals classified as independent by the NLSY97 in a given year; third, we keep individuals between the ages of 18 and 23 during the years from 1997 to 2003; and, fourth, we require that we observe parental income tercile. This leaves 8,907 individual-year observations (3,384 individuals).

A.1.2 Estimations related to beliefs, college enrollment, and robustness exercises

Predicting BA enrollment by age 30: probit regression coefficients Table A1 reports probit regression coefficients whose Average Marginal Effects are reported in Table 2 of Section 2, as well the pseudo-R^2.

Table A1: BA enrollment by age 30: regression coefficients

Controls	**(1)**	**(2)**
Expected probability of earning a BA by age 30	1.428	1.409
	(0.116)	(0.146)
Skill	0.0215	0.0186
	(0.00116)	(0.00145)
Female	0.193	0.219
	(0.0606)	(0.0732)
Age in 1997	-0.0368	-0.0518
	(0.0216)	(0.0263)
Logged real parental income in 1997		0.130
		(0.0432)
At least one parent BA+ in 1997		0.419
		(0.0885)
Constant	-1.619	-2.799
	(0.344)	(0.583)
pseudo-R^2	0.237	0.268
Obs	2,222	1,606

Notes: Table A1 shows point estimates for probit regression coefficients whose Average Marginal Effects are reported in Table 2 of Section 2. Sample: model (1) is high school graduates; model (2) is high school graduates, conditional on observing parental income and parental education. Standard errors are in parentheses. Source: NLSY97.

The distribution of expected graduation probabilities Table A2 shows the distribution of beliefs within each skill tercile, where skill terciles are assigned using the distribution of ASVAB percentile scores in the cleaned sample. Specifically, for the sample of high school graduates, Panel A reports the fraction of a given skill tercile that responded with an expected probability within a given range; the skill tercile is assigned a row, and the expected probability range is shown in the column header. Each row of Panel A sums to one. In all terciles, the plurality of respondents give values between 80 and 100, although the lowest skill tercile also has a large mass reporting a likelihood between 40 and 59. However, note that no skill level has a mass of 0 in any column. Additionally, reported values within a given interval are not uniformly distributed; this is shown in Panel B, which demonstrates that the average value for a given skill tercile is not the midpoint of the column's interval. In particular, for responses between 80 and 100 percent, the average value is very close to 100 percent, while for responses between 0 and 19 percent the average probability is closer to the lower bound of that interval.

Table A2: Discretized distribution of beliefs among high school graduates

Panel A:		**Expected probability of earning BA**				
Distribution	**Skill**	*0 to 19*	*20 to 39*	*40 to 59*	*60 to 79*	*80 to 100*
	1	0.088	0.071	0.220	0.124	0.497
	2	0.055	0.040	0.136	0.170	0.599
	3	0.023	0.014	0.058	0.102	0.803
Panel B:		**Expected probability of earning BA**				
Mean values	**Skill**	*0 to 19*	*20 to 39*	*40 to 59*	*60 to 79*	*80 to 100*
	1	3.631	24.434	49.270	71.609	96.062
	2	4.195	25.167	48.644	71.865	96.699
	3	7.000	24.500	49.791	72.107	95.988
	Obs	2,222				

Notes: Panel A of Table A2 reports the fraction of each skill bin (rows) with reported beliefs in a given interval (columns); the values in each row sum to 1. Panel B reports, for the row's skill tercile, the average belief for responses within each column's interval in units of percentages. Source: NLSY97.

Educational attainment expectations for youth and parent: comparison within families Table A3 reports the difference between student and parent expected probabilities of obtaining a BA, within the same family, when both respondent and parent expectations about respondent educational attainment are reported (parent beliefs are only reported with valid responses for a subset of the student beliefs sample). The results are reported seperately by whether the child later enrolled in a BA (Panel A) or not (Panel B). Regardless of enrollment outcome, the average expected probabilities of parents and children in the same family tend to agree: the median difference is 0. Percentiles of the distribution of differences other than the median (p50) are also reported in the table and indicate the the distribution is largely symmetric around 0. These results support our modeling assumption that parents have the same subjective beliefs as their child.

Table A3: Moments of the distribution of within-family difference in beliefs

Panel A: College enrollees	**Skill**	**Obs**	**mean**	**p10**	**p25**	**p50**	**p75**	**p90**
	1	136	5.31	-40	-5	0	25	50
	2	293	2.44	-25	-1	0	10	25
	3	447	0.21	-20	-5	0	5	20
	Obs	876						
Panel B: Non-enrollees	**Skill**	**Obs**	**mean**	**p10**	**p25**	**p50**	**p75**	**p90**
	1	379	6.27	-40	-10	0	25	50
	2	244	1.57	-40	-15	0	20	50
	3	125	1.28	-25	-10	0	10	35
	Obs	748						

Notes: Table A3 shows statistics on the distribution of within-family differences between parent and child expected probabilities of the child earning a BA. Samples: Panel A, students who enrolled in a BA program before age 30, whose parents responded to the beliefs question; Panel B, students who did not enroll in a BA program before age 30, whose parents responded to the beliefs question. Source: NLSY97.

College enrollment rates Table A4 reports enrollment rates by age 25 and by age 30 in the NLSY97 for each skill tercile and overall, where skill terciles are assigned using the distribution of ASVAB percentile scores in the cleaned sample. Most college enrollment happens before age 25. We use an indicator for enrollment by age 30 to compare true graduation rates with expectations because this aligns with the wording of the expectations question in the NLSY97 questionnaire. For the enrollment rates used as calibration targets, enrollment by age 30 is not an intuitive mapping to the one-time enrollment choice consumers make at age 18 in the model. Since the model allows this choice to be made once immediately after high school graduation, but in reality young people may wait a few years after high school before enrolling in college, using enrollment by age 18 in the data is not satisfactory either. We therefore use enrollment by age 25, between these two ages, as the calibration target.

Table A4: Bachelor's degree program enrollment rates by skill tercile and overall

Skill	Enrolled by age 25	Obs	Enrolled by age 30	Obs
1	22.92	685	26.95	742
2	50.29	680	55.99	743
3	76.70	691	79.24	737
Total	50.05	2,056	54.01	2,222

Notes: Table A4 shows enrollment rates in a 4-year degree program by age 25 and by age 30, for each skill tercile. Skill terciles are assigned using the distribution of skill among high school graduates. Enrollment rates computed for the same sample. Source: NLSY97.

Table A5 shows enrollment rates by age 25 broken down by parental income income tercile and skill tercile, where both parental income tercile and skill tercile are assigned using the distribution of each variable in the cleaned sample conditional on observing the respective variable. Requiring a valid parental income value reduces the sample size. We use enrollment rates by skill for the highest income tercile as a target in our model calibration of the enrollment option shock because we view that group as least affected by financial constraints.

Table A5: Bachelor's degree program enrollment rates by skill and parental income terciles

Income:	1		2		3	
Skill	Enr. rate	Obs	Enr. rate	Obs	Enr. rate	Obs
1	16.12	273	25.93	162	35.71	70
2	44.44	153	48.04	179	56.50	177
3	58.95	95	68.66	201	87.75	253
Obs	1,563					

Notes: Table A5 reports the enrollment rate in 4-year program by age 25, by skill tercile (rows) and parental income tercile (columns). Enrollment rates are in percentages. Sample is high school graduates for whom parental income is also observed. Source: NLSY97.

Educational attainment outcomes versus expectations: breakdowns In Table A6 we report the within-skill-tercile average expected graduation rate, realized graduation rate, and the difference between these (the extent of optimism) by respondent gender and skill tercile (Panel A) and by parental education and respondent skill tercile (Panel B). As elsewhere, skill terciles are assigned using the distribution of ASVAB percentile scores in the cleaned sample. In Panel A, we see that the difference across genders within each skill bin is not sizable. In Panel B, we see that parental education is more predictive of optimism than gender, where parental education is defined as whether or not the respondent has at least one parent with a BA or higher. Within a skill bin, respondents without a highly educated parent tend to be more optimistic. As for monotonicity within each parental education group, the lowest skill tercile exhibits optimism, but to a slightly less extent than the middle tercile. Note, however, that the sample size for the lowest skill tercile in families with highly educated parents is only 40 individuals, so the standard error of the average extent of optimism in that bin is large. This makes drawing conclusions about how optimism is related to skill within the highly educated group problematic; we cannot reject monotonicity due to the large standard errors in this portion of the panel.

Table A6: Subjective beliefs about BA attainment among college enrollees: breakdowns

Panel A: by student gender and skill	**Female**	**Skill**	**Obs**	(a) **Expected prob. BA by 30**	(b) **Realized graduation rate**	**Difference** $(a)-(b)$
	No	1	83	82.23 (2.80)	39.76 (5.40)	42.47 (6.09)
		2	160	81.94 (1.94)	54.38 (3.95)	27.56 (4.40)
		3	261	89.70 (0.98)	78.16 (2.56)	11.54 (2.74)
	Yes	1	117	79.61 (2.70)	47.01 (4.63)	32.60 (5.36)
		2	256	90.15 (1.16)	60.94 (3.06)	29.21 (3.27)
		3	323	93.56 (0.77)	76.16 (2.37)	17.40 (2.49)
	Obs	1,200				

Panel B: by parental ed. and skill	**At least one parent BA+**	**Skill**	**Obs**	(a) **Expected prob. BA by 30**	(b) **Realized graduation rate**	**Difference** $(a)-(b)$
	No	1	141	80.52 (2.35)	41.84 (4.17)	38.67 (4.78)
		2	263	85.39 (1.43)	51.33 (3.09)	34.06 (3.40)
		3	261	89.89 (1.07)	68.20 (2.89)	21.69 (3.08)
	Yes	1	40	83.92 (3.93)	70.00 (7.34)	13.93 (8.32)
		2	126	90.61 (1.57)	72.22 (4.01)	18.39 (4.30)
		3	309	93.57 (0.67)	84.47 (2.06)	9.10 (2.17)
	Obs	1,140				

Notes: Table A6 compares expectations and outcomes across skill terciles by student gender and parental education level. Panel A is students who enrolled in a BA program before age 30, and Panel B is students who enrolled in a BA program before age 30 and for whom parental education is observed. Source: NLSY97.

Summary statistics: enrollees who expect BA with certainty Table A7 reports summary statistics for the sample who expect to earn a BA with 100 percent probability (certainty), and who also enroll in college. The realized graduation rate is 69 percent, which makes the extent of optimism about the likelihood of graduation likelihood is 31 percentage points. For this group, the observed optimism is optimism about graduation likelihood specifically because their intent to attend a BA is 100 hundred percent. This group accounts for 28 percent of all high school graduates.

Table A7: BA enrollees who expect to earn a BA with certainty

Variable	**Mean**
Enr BA by 30	100.00 (0.00)
Pr. BA by 30 (youth)	100.00 (0.00)
BA by 30	69.11 (1.86)
ASVAB	62.29 (1.01)
Female	0.64 (0.02)
Age beliefs response	15.89 (0.03)
Age in 1997	15.05 (0.06)
Family real income in 1997	96,078 (3,494)
At least one parent BA+ in 1997	0.44 (0.02)
Obs	615
Sample share	0.28

Notes: Table A7 reports summary statistics for the sample who expect to earn a BA with 100 percent probability (certainty). SEs in parentheses. Source: NLSY97.

The distribution over skill endowment terciles by parental education Table A8 reports the initial joint distribution of child skill, measured with the assigned ASVAB tercile, and parental education in the sample of high school graduates. Skill terciles are assigned using the distribution of ASVAB percentile scores in the cleaned sample. We use this table to parameterize the sensitivity analysis where child skill endowments are allowed to be correlated with parental education, whose results are reported in Appendix D.4.

Table A8: Initial skill distribution by parental education

	Skill tercile		
At least one parent BA+	1	2	3
No	0.405	0.350	0.245
Yes	0.136	0.285	0.579
Obs	2,104		

Notes: Initial joint distribution of skill and parental education. Sample: high school graduates for whom we also observe parental education (which reduces the number of observations slightly compared to Table A4). Source: NLSY97.

A.1.3 Estimation of earnings process and the college wage premium

Earnings process components and functional forms The earnings process we use in our structural model realizes a quantity of efficiency units at each age j. This quantity has a deterministic component, $\epsilon_{j,e,s}$, and a stochastic component, η. The deterministic component depends on the consumer's age, j, their education, e, and their skill endowment, s:

$$\epsilon_{j,e,s} = \exp\left(\beta^A_{e,1} j + \beta^A_{e,2} j^2 + \beta^A_{e,3} j^3 + \beta^s_{e,s}\right)$$

The stochastic component is an AR(1) process where the persistence parameter ρ_e depends on the consumer's educational attainment, as does the variance σ^2_e of the Normal distribution from which the error term is drawn:

$$\begin{aligned} \eta^{'} &= \rho_e \eta + \nu_e \\ \nu_e &\sim \mathbb{N}\left(0, \sigma^2_e\right) \end{aligned}$$

In order to estimate the earnings process for each education category e, we implement an approach based on that of Abbott, Gallipoli, Meghir, and Violante (2019), with modifications to suit our model specification. First, we use the Panel Study of Income Dynamics (PSID) to estimate how logged real wages depend on a third-order polynomial of age for a given education group, $e = \ell$ (HS or some college) or $e = h$ (BA or higher). This identifies $\beta^A_{e,1}$, $\beta^A_{e,2}$, and $\beta^A_{e,3}$ for each education group e. We use the PSID rather than the NLSY97 to estimate the age polynomial because it allows us to see a more complete life cycle of earnings than is visible in the NLSY97 due to the latter survey's shorter panel dimension. Next, we take logged hourly real wages in the NLSY97, clean them of age effects with the PSID estimation results, and regress the resulting age-free log hourly real wages on indicators for skill terciles. The coefficients on skill tercile indicators are the factor loadings on skill s for a given education e, $\beta^s_{e,s}$. Finally, using the residuals from the NLSY97 regression, we jointly estimate ρ_e and σ^2_e for each education group. Point estimates are reported in Table A9.

Estimating age profiles in the PSID Our raw extract excludes the SEO census sample, contains 34,856 individuals and 2,930 families, and covers the period from 1968 to 2019. The PSID collects data on the household head and, if present, their resident spouse (Survey Research Center, Institute for Social Research, 2021). We use information on the educational attainment of the household head and resident spouse (if any), as well as each individual's sex, total income, total income from transfers, total labor earnings, labor component of business income, hours worked, marital status (a flag equal to 1 if married with spouse present, 0 if not) and employment situation (which is used to identify the self-employed). Using this information, we construct unearned income as total income net of earnings and transfers. We construct hourly wages by dividing the individual's labor earnings by total hours worked for the individual. Note that the labor component of business income is not included in labor earnings for some years of the PSID. For years when it is not included, we manually add it to reported labor earnings. We correct all income and wage variables for inflation by converting to 2016 dollars using the CPI (BLS, 2021) and thereafter use real dollar values in our analysis. We then reshape the data into an individual-level panel where each male or female adult in the household is followed over time.

We drop observations for whom we do not observe state of residence, marital status, or sex of the household head. We compute annual real wage growth and drop observations with growth higher than 4 percent or less than -2 percent, or where the level of real wages exceeds 400. We then restrict the sample to those aged 65 and younger who are aged greater than 17 for those with 12 years of education, greater than 19 for those with 13 to 15 years of education (some college or associate's degree), and greater than 21 for those with 16 or more years of education. Next, we drop those who are self-employed. We then count the number of times an individual is observed in our panel, and drop individuals observed fewer than eight times. In our estimation of age profiles, we assign those who earn between 12 and 15 years of education into the "high school" group; those who earn 16 years or more of education are in the "BA" group. These definitions mean that those who have some college or an associate's degree are assigned to the high school group in our estimation procedure. Using this estimation sample, we proceed in two stages to account for selection into working within each education category, described below. The estimation sample for the second stage has 73,182 individual-year observations (4,965 individuals) for the high school group, and 52,877 (3,574 individuals) for the BA group.

In the first stage, we regress an indicator for working positive hours on an age polynomial and a set of standard controls, X, that includes a constant, an indicator for being married, a set of dummies for the year, and a set of dummies for the state of residence, for those with a given educational attainment. In addition to the standard controls, in the first stage we also control for Z, which is unearned real income. This first-stage regression can be written as

$$\mathbb{I}_{hrs>0} \quad = \quad \alpha^A_{e,1} age + \alpha^A_{e,2} age^2 + \alpha^A_{e,3} age^3 + \gamma_{e,Z} Z + \vec{\alpha}_e X + \epsilon$$

where ϵ is the residual. This first-stage regression is estimated using a probit estimator, and the result is used to construct an inverse Mills ratio. The second-stage regression that has all of the same controls as the first stage, but with unearned income replaced with the estimated inverse Mills ratio, IM, from the first stage. In this second stage regression, the dependent variable is the log of the real wage, w, and we use an Ordinary Least Squares (OLS) estimator. This regression estimated on a given education group can be written as

$$w \quad = \quad \beta^A_{e,1} age + \beta^A_{e,2} age^2 + \beta^A_{e,3} age^3 + \gamma_{e,IM} IM + \vec{\gamma}_e \times X + u$$

where u is the i.i.d. residual. The age profile of education e is given by $\beta^A_{e,1}$, $\beta^A_{e,2}$, and $\beta^A_{e,3}$. Note that, because the average rejected wage offer is likely lower than the average accepted wage offer, the expected sign of the inverse Mills ratio coefficient in the second stage, $\gamma_{e,IM}$, is positive. In our estimation, this coefficient has the expected sign for both education groups.

Estimating skill loadings in the NLSY97 This estimation is performed on the sample described in A.1.1; using the estimated age contributions to log wages from the PSID, we log real wages in the NLSY97 and, using the observation's associated age, clean logged real wages of their estimated age component. The resulting "age-free" log wages, w_{AF}, are then regressed on dummies for skill terciles, as well as a vector X of controls that include dummies for the year and number of children (top-coded at 4), an indicator for being married, and a control for being in the supplemental sample for the NLSY97. For each education level e, the estimation equation can be written as

$$w_{AF} \quad = \quad \beta^s_{e,0} + \beta^s_{e,s} \times i.\,[\text{Skill tercile} = s] + \chi X + u$$

where u is the i.i.d. residual. The estimated skill loadings are given by $\beta^s_{e,s=1}$ and $\beta^s_{e,s=2}$ for the first and second skill terciles, respectively (where the highest tercile is the baseline level).

Estimating the AR(1) process using NLSY97 regression residuals After estimating the skill loadings in the NLSY97, we use the residuals of that regression as inputs to estimate an AR(1) shock process for each education category. For each education group, this process is characterized by two parameters. Given a guess of parameters, we construct a variance-covariance matrix between lags of the residual component and compare it with an analogous matrix constructed on the empirical residuals. We iterate on the parameter guess until the two matrices converge. In our estimation, we use 500 bootstraps. For each education level e, the persistence and variance of the AR(1) process are given by ρ_e and σ^2_e, respectively.

Summary of earnings process estimation results Table A9 presents the results of the earnings process estimation. We find that earnings increase at a decreasing rate over the life cycle, that the return to skill is higher for college graduates, and that the stochastic component of the earnings process is less persistent for those with more education (although random-shock variances are slightly higher).

College wage premium by skill tercile Table A10 reports the median real wage within each skill tercile by education group using the estimation sample for skill loadings (which is a panel at the individual-year level). The last column of the table is the college wage premium, which is the ratio of the two medians within each skill tercile. The wage premiums reported here are compared with their untargeted model counterparts in Table A21 of Appendix C.

Table A9: Earnings process estimation results

Category	Parameter	Estimation data	Value given education e: $e=\ell$	$e=h$
Panel A: Age third-order polynomial	$\beta^A_{e,1}$	PSID	0.0959	0.1890
	$\beta^A_{e,2}$		-0.00151	-0.00332
	$\beta^A_{e,3}$		0.00000695	0.0000190
Panel B: Skill endowment tercile shifter	$\beta^s_{e,1}$	NLSY97	-0.179	-0.243
	$\beta^s_{e,2}$		-0.0641	-0.102
Panel C: AR(1) persistence and variance	ρ_e	NLSY97 regression residuals	0.904205	0.886040
	σ^2_e		0.051526	0.072137

Table A10: Bachelor's degree wage premium by skill tercile: ratio of median wages

	High school		**Bachelor's degree**		
Skill	**Real wage**	**Obs**	**Real wage**	**Obs**	**Wage premium**
1	13.71	7,414	18.55	1,013	1.35
2	15.99	5,760	22.05	2,706	1.38
3	17.16	3,186	25.20	5,687	1.47

Notes: Table A10 tabulates the median wage within skill tercile for those with a high school degree but less than a bachelor's degree ("High school") and those with a bachelor's degree or higher ("Bachelor's degree"), for those not currently enrolled in post-secondary education. Wages are in 2016 USD. The last column is the ratio of median wages in the two educational attainment categories, the college wage premium. Observation counts are at the individual-year level. Source: NLSY97.

Robustness: age polynomial for "some college" As a check on our model specification, we also estimate the effect of some college or an associate's degree, relative to only a high school degree, on the age profile of earnings in the PSID by running the same regression as our main specification but augmented with the interaction of a flag for some college, $\mathbb{I}_{\text{SC}}$, with the age polynomial. Results for the interaction terms of this estimation are presented in Table A11; these coefficients are statistically insignificant.

Table A11: Robustness on pooling assumption for log wages as a function of age

Controls	**log(wage)**	**SE**
$\mathbb{I}_{\text{SC}} \times$ age	0.0230	(0.0153)
$\mathbb{I}_{\text{SC}} \times$ age^2	-0.000309	(0.000388)
$\mathbb{I}_{\text{SC}} \times$ age^3	0.000000839	(0.00000314)
$\mathbb{I}_{\text{SC}}$	-0.307	(0.194)
R^2	0.111	
Obs	73,182	

Notes: Table A11 reports regression results. Not shown but included as controls: uninteracted age polynomial, state and year FE, flag for married, inverse Mills ratio, constant. Source: PSID.

A.1.4 Estimation of inter vivos transfers

This estimation is performed on the relevant sample described in Section A.1.1 and is based on that of Abbott, Gallipoli, Meghir, and Violante (2019). To account for an implicit transfer from parents to their children who cohabit with them and do not pay rent, we flag those cohabiting with their parents and paying no monthly rent, then impute the average monthly rent paid by sample members with the same parental (family) income tercile, college enrollment status, and observation year who are not cohabiting. Next, we transform monthly rent to yearly rent, and add it to yearly net income received from parents (if both parents are present) or from both the mother and father (if both parents are not present). We also add any yearly allowances received. The resulting quantity is the yearly nominal transfers from parents to their child. Within each year, we then multiply the quantity by 6 and divide by nominal GDP per capita in that year (for those over 18) to find a unitless implied ratio of transfers received to per capita income for each individual while they are young adults of college age. We then average this ratio across invididuals and years to find the value reported in the first row of Table A12. The average real values of the components of transfers are also reported.

Table A12: Inter vivos transfers

Variable	Mean
Transfer ratio	0.589
Transfers	6,683
Transfers not allowance	693
Allowance	178
Imputed rent	6,761
Obs (invidual-year)	8,907
Obs (inviduals)	3,384

Notes: Table A12 reports average transfers for the sample used to estimate inter vivos transfers. Sample: independents between 18 and 23 observed during 1997-2003. Transfer amounts are in 2016 USD. Data are at the individual-year level. Source: NLSY97.

A.2 The High School Longitudinal Study of 2009

The High School Longitudinal Study of 2009 (HSLS:09) is a representative panel of ninth-grade students in the United States beginning in 2009 who attended high schools that had both ninth and eleventh grades (National Center for Education Statistics, U.S. Department of Education, 2020a). We use the public version of the HSLS:09, where this information is reported up to and including the 2015-2016 academic year (Duprey et al., 2020).

The structure of the HSLS:09 is complex. Waves of the study occur in the fall of 2009, in the spring of 2012 (first follow-up), in the summer of 2013 (2013 update), and in the spring of 2016 (second follow-up). High school transcripts are collected during the 2013-2014 academic year, and post-secondary transcripts (as well as student records) are collected in the 2015-2016 academic year (after potentially three full years of academic enrollment in post-secondary education). The second follow-up in the spring of 2016 includes information from students who are currently enrolled in post-secondary education, as well as those who are not enrolled but used to be, and those who did not pursue post-secondary education. If sample members begin a four-year BA degree program in the fall after high school graduation (the fall of 2013) and do not take any time off from school, then they complete the second follow-up questionnaire in the spring of their third year of college and student records are available up to and including this third academic year (2015-2016). Regardless of postsecondary persistence status, survey information about the focal sample member includes their honors-weighted high school GPA (our measure of skill in this dataset), as well as any financial aid and private loans they took out to pay for post-secondary education. We use this variable to measure skill because we consider it the variable closest in information content to the ASVAB measure used for our analyses of NLSY97 data (we do not observe ASVAB scores in the HSLS:09). Note that honors-weighted GPA takes into account whether a course is honors or college level, and then makes an adjustment to how the grade contributes to overall GPA accordingly. For a given letter grade, this adjustment raises the assigned GPA if the difficulty of the courses taken is higher. See HSLS:09 2013 Update: Student file codebook and HSLS:09 2013 Update User Manual Appendix for the specific formulas used to compute honors-weighted high school GPA in the HSLS:09. Information on federal financial aid (loans and grants) and private loans are also collected from institutions themselves in the post-secondary transcripts and student records data collection wave. Our estimations use variables based on student record information, when available.

A.2.1 Estimation sample

To begin, we restrict our sample to respondents who earn a high school diploma by the summer of 2013 and enrolled in a BA program in the fall of 2013. We also require that, for each youth respondent in our sample, we observe gender, parental income in the first or second wave, that the respondent be living with at least one biological parent, that we observe biological parental educational attainment while the respondent is in high school, and that we observe the sample member's honor's-weighted high school GPA. We also require that the respondent reports their educational attainment expectations in the spring of their junior year of high school. If we observe parental (family) income in both the base year and first follow-up of the HSLS:09, we use the average of these income values as the real parental income level for that sample member after converting to 2016 USD using the CPI (BLS, 2021). Finally, we require that we observe the respondent in the second follow-up survey. We use this sample of 11,444 individuals to assign skill and parental income terciles using second follow-up student longitudinal weights.

Next, we generate BA enrollment and persistence flags using administrative records collected from postsecondary institutions by the HSLS:09. Specifically, to be counted as enrolled in a BA in the fall of 2013, we require that the institutional records be nonmissing, and that they indicate that the respondent is enrolled at a 4-year institution and that they be pursuing at least 20 credits in their first academic year of enrollment (in the fall of 2013). To be counted as a persister by 2016, the sample member must have been flagged as an enrollee in 2013 and additionally remained enrolled in a 4-year program and attempted at least 20 credits each academic year. Respondents also count as persisting if they were flagged as enrolling in the fall of 2013 and are observed to have earned a bachelors degree by 2016. We identify 2,356 individuals who are BA enrollees in the fall of 2013 and 1,855 enrollees who persisted in a BA as of 2016.

A.2.2 Estimations related to model parameterization and robustness exercises

Grants as a share of tuition and fees Table A13 reports moments computed by skill tercile in the HSLS:09 used to discipline our quantitative model; here, we assign skill terciles using the distribution of honors-weighted high school GPA among high school graduates. The first column reports the average tuition and fees paid by each skill tercile of fall 2013 college enrollees in current dollars. The second column is the ratio of aggregate grants to aggregate tuition and fees within each skill tercile during the first academic year of enrollment. This ratio is used to compute the subsidy rate from public and private grants reported in Table 6 of the main text.

Table A13: Statistics by skill tercile

Skill	Tuition + Fees	$\frac{\text{Agg Grants}}{\text{Agg Tuition + Fees}}$
1	17,032	0.403
2	17,726	0.462
3	19,960	0.520
All	18,997	0.494
Obs	2,356	

Notes: Table A13 shows statistics by skill tercile for tuition and fees in 2013 USD and grants as a fraction of tuition and fees during the first academic year; dollars are current dollars and skill is measured using honors-weighted high school GPA. Sample: 2013 enrollees. Weights are PETS-SR student records longitudinal weights. Source: HSLS:09.

Labor supply of college enrollees and reasons for not enrolling Table A14 reports moments describing average labor supply among college enrollees and reasons for not enrolling in post-secondary education. The average time spent working per week in their third academic year for fall 2013 enrollees is expressed as a fraction of full-time work (40 hours). The last three rows of this table report suggestive evidence for why students never enroll in post- secondary education to motivate the introduction of the enrollment option shock, $q(s)$, in the quantitiative model. This evidence uses responses to the question "why did you never enroll in college?". Note that, in this survey question (unlike in the main text and this appendix generally), "college" refers to *any* post-secondary education, and respondents are only asked this question if they say that they never enrolled in college. This means that those who never enroll in a four-year degree program but who enroll in another type of post-secondary program are not asked this question, so it is not capturing reasons for not enrolling in a BA in particular. Even conditioning on being asked, non-response rates are high. We examine the sample of survey respondents who graduated from high school in 2013 and either did not enroll in any postsecondary education and aswered the question about reasons for not enrolling, or enrolled in a 4-year degree in the fall of 2013; enrollees are counted as answering 'No' for each possible reason for not enrolling, and Table A14 reports the share of the sample answering "Yes' for the reason of that row. When presented with a menu of possible reasons for not enrolling, 32 percent of those who either enrolled in no postsecondary education or enrolled in a 4-year BA program indicate that factors such as academics, family, or other reasons that do not include financial or work factors are part of what led them to them not enrolling in post-secondary education (respondents may select more than one reason).

Table A14: Labor supply and reasons for never enrolling

Category	**Variable**	**Value**	**Sample obs**
Labor supply junior year	$\frac{\text{Average weekly hours worked}}{40}$	0.347	1,855
Reason never enrolled in post-secondary ed. (answered "yes" for a given reason)	Academic, personal/family, other	0.316	4,262
	Financial	0.245	
	Work, military, career	0.190	

Notes: Table A14 reports labor supply and reasons for never enrolling in a post-secondary program. Samples: first row is students who enrolled in a 4-year program in the fall of 2013 and persisted through their third academic year; remaining rows are sample members who graduated from high school in 2013 and either did not enroll in any postsecondary education or enrolled in a 4-year degree in the fall of 2013, and aswered the question about reasons for not enrolling; enrollees are counted as answering 'No' for each possible reason; values are shares answering "Yes' for a given reason. Weights are PETS-SR student records longitudinal weights for the first row and second follow-up student longitudinal weights for the remaining rows. Source: HSLS:09.

Predictors of college enrollment persistence Table A15 presents a set of probit estimator estimation results for a model where the dependent variable is an indicator for persisting to the third academic year on various attributes of the student in the first year; the sample is 2013 BA enrollees. The table reports regression coefficients and Average Marginal Effects in the first and second column, respectively. These results indicate that honors-weighted high school GPA plays a statistically significant role in predicting persistence in one's college career, even controlling for parent attributes (parental income and parental education) and college enrollee attributes (debt, hours worked, gender) and institution attributes (tuition and fees in first institution attended). In our controls, we convert dollar values for parental income, first year student debt, and first year tuition and fees into 2016 USD using the CPI. Other than GPA, no other control is statistically significant at the 1 percent level. These results are part of the motivation for our model specification linking the probability of being allowed to continue in college, $p(s)$, to student skill, s.

Table A15: Predicting enrollment persistence (probit estimator)

	Coefficients	**Margins**
High school GPA	0.47788	0.14526
	(0.09414)	(0.02815)
Log(Real parental income	-0.01986	-0.00604
	(0.08747)	(0.02653)
Log(Real SL debt)	0.05205	0.01582
	(0.18127)	(0.05508)
Hours worked	-0.01796	-0.00546
	(0.00978)	(0.00297)
Log(Real tuition and fees Y1)	0.06569	0.01997
	(0.09198)	(0.02830)
Flag: no SL debt	0.61830	0.19446
	(1.56553)	(0.48995)
Flag: no work hours	-0.35549	-0.10435
	(0.21377)	(0.05983)
Flag: parents BA+	0.28075	0.08680
	(0.11989)	(0.03764)
Flag: female	0.08965	0.02734
	(0.10311)	(0.03172)
Constant	-1.68471	
	(1.93409)	
F-test	8.102	
Obs	2,356	

Notes: Table A15 reports Average Marginal Effects computed from regressing an indicator for persisting to their third academic year on various controls measured in the first academic year using a probit estimator. Sample: students who enrolled in a four-year program in the fall of 2013 (Y1). Household income and first year student debt and tuition and fees are in 2016 USD. Bootstrap standard errors are in parentheses; weights are PETS-SR student records longitudinal weights. Source: HSLS:09.

Educational attainment expectations versus outcomes In the first follow-up wave (collected during the spring of the respondent's junior year of high school) the HSLS:09 asks respondents about their expected educational attainment. Unlike the phrasing of a similar question in the NLSY97, the phrasing of the question in the HSLS:09 on expected educational attainment is not probabilistic: the specific wording of the question when posed to students is "As things stand now, how far in school do you think you will actually get [in your education]?" The survey also asks the same question of the student's parent about their child's prospects. The possible answers range from 1 ("Less than high school completion") to 12 ("Complete a PhD"), with 13 "Don't know" as an optional response. The HSLS:09 is not our preferred source for beliefs about education outcomes for two main reasons: first, there is no age limit condition on the outcome being asked about; and, second, the response is categorical rather than a continuous probability. For example, because of the short panel dimension of the HSLS:09, we cannot definitively say if they permanently drop out of college or fail to ever enroll during the course of their life (which is what the HSLS:09 expectations question is asking).

To flag those who expect to complete a four-year BA program, an indicator is created that is set to 0 for responses between 1 and 13 ("Don't Know" is a valid response) and replaced with a 1 if the response x is such that $8 \leq x < 13$, that is expect to complete a BA or higher. An indicator for those who expect to enroll in a master's degree or higher is constructed a similar way, but with the lower bound starting at 10 ("Start a Master's degree"). Subsequently, we are able to verify whether the sample members enroll in a four-year BA program after high school and whether they persisted in their program after enrollment. With this information, we examine the relationship between respondent skill (high school honors-weighted GPA) and educational outcomes (both expected and realized).

Panel A of Table A16 presents, by skill tercile, the percentage of each bin that expected to complete a BA program and the percentage of the bin that persisted in a 4-year BA program until their third academic year (or completed the BA as of that time). In particular, Panel A of Table A16 indicates that the sample of students who enroll in a four-year program in 2013 tend to overestimate their educational attainment, given their skill. This is especially the case for those in the lowest skill tercile.

A concern with the findings reported in Panel A of Table A16 is that respondents claim they will get a BA to avoid a utility cost, which may generate a "social desirability bias" in the survey responses. To address this concern, in Panel B we show a tabulation restricting to those who expect to attend a master's (MA) degree or higher. Note that, by implication, in this group everyone expects to get a BA. This eliminates students who are fibbing in their responses that they expect to earn a BA or more because of stigma costs, by dropping those right on the threshold of admitting they won't get a BA. It seems less likely that stating you expect to begin an MA or more, relative to a BA, is driven by fear of stigma costs. The tabulation demonstrates that the percentage who persist in each tercile still remains well below the expected graduation rate from college, especially for the lowest skill tercile.

Finally, in Panel C of Table A16, we tabulate the parent responses to what they expect their child's educational attainment will be. Note that the sample size of families with responses to this questionnaire is much smaller than the sample of valid student responses because the parent questionnaire was only administered to a random sample of 48 percent of families in the sample. Parents tend to overestimate the likelihood of BA attainment for their children, especially when their child belongs in a lower skill tercile.

Table A16: Educational attainment outcomes versus expectations

Description	Skill	Obs	% Expected BA	% Persisted BA	Difference
Panel A: Fall 2013 enrollees	1	152	76	47	29
	2	668	80	71	9
	3	1536	93	83	10
Panel B: Expect MA+	1	55	100	43	57
	2	315	100	69	31
	3	986	100	83	17
Panel C: Parent expectations	1	60	76	38	38
	2	284	92	71	21
	3	677	94	81	13

Notes: Table A16 compares realized and expected bachelor's degree attainment probabilities in fractions. Samples vary across panels as described in the table. Weights are PETS-SR student records longitudinal weights. Source: HSLS:09.

A.3 CBO income statistics

In order to estimate the degree of income tax progressivity, τ_p, we use aggregate data on the distribution of household income published in "The Distribution of Household Income" by the Congressional Budget Office (CBO) for 2016, 2017, and 2018 (U.S. Congressional Budget Office, 2019, 2020, 2021); specifically, we apply the estimation method of the robustness exercise described in Heathcote, Storesletten, and Violante (2017) to data underlying Figures 1, 3, and 4 of those annual reports. Table A17 compiles the data for the three years we use in our estimation. The specific figures within each CBO report whose underlying data provides the empirical moments for the corresponding year are: for column (1), Figure 4; for columns (2)-(4), Figure 3; and, for column (6), Figure 1.

A.3.1 Estimation sample

Table A17 reports the baseline federal tax rate, as well as the transfer rates from Temporary Assistance to Needy Families (TANF), Supplemental Nutrition Assistance Program (SNAP), and Supplemental Security Income (SSI) shown in columns (1), (2), (3), and (4), respectively. We compute the empirical equivalent of the net tax rate for our model as the federal tax rate (which includes refundable credits as reported in column 1) minus the transfer rates from TANF, SNAP, and SSI and report this net tax rate in column (5). Average pretax income in column (6) is logged in column (7); logged after-tax income reported in column (8), where after-tax income is computed by taking the log of the net tax rate in column (5) applied to the pretax income of column (6).

Table A17: CBO data by year

Year	Percentiles Min	Max	(1) Fed. tax	(2) TANF	(3) SNAP	(4) SSI	(5) Net tax	(6) Ave. Y	(7) $\log(Y)$	(8) $\log(Y_{AT})$
2016	99	100	33.3				33.3	1.789	0.25	0.08
	96	99	26.8				26.8	0.360	-0.44	-0.58
	91	95	23.6				23.6	0.218	-0.66	-0.78
	81	90	21.2				21.2	0.160	-0.80	-0.90
	60	80	17.9				17.9	0.110	-0.96	-1.04
	40	60	13.9	0.5			13.4	0.072	-1.14	-1.21
	20	40	9.4	2.0	1.2	0.9	5.3	0.045	-1.35	-1.37
	0	20	1.7	10.1	8.4	6.4	-23.2	0.021	-1.68	-1.59
2017	99	100	31.6				31.6	1.960	0.29	0.13
	96	99	26.5				26.5	0.380	-0.42	-0.55
	91	95	23.4				23.4	0.230	-0.64	-0.76
	81	90	21.3				21.3	0.170	-0.78	-0.88
	60	80	17.9				17.9	0.110	-0.95	-1.03
	40	60	14.0	0.5			13.5	0.080	-1.12	-1.19
	20	40	9.2	2.0	1.1	0.9	5.2	0.050	-1.34	-1.36
	0	20	1.3	9.7	8.1	5.9	-22.4	0.020	-1.68	-1.59
2018	99	100	30.2				30.2	2.000	0.30	0.14
	96	99	24.2				24.2	0.400	-0.40	-0.52
	91	95	21.9				21.9	0.240	-0.62	-0.73
	81	90	20.0				20.0	0.170	-0.77	-0.87
	60	80	16.7				16.7	0.120	-0.92	-1.00
	40	60	12.8				12.8	0.080	-1.10	-1.16
	20	40	8.1	1.6	0.9	0.8	4.8	0.050	-1.30	-1.32
	0	20	0.05	9.2	6.9	5.9	-21.95	0.020	-1.70	-1.61

Notes: Table A17 reports the components for the estimation of the income tax progressivity parameter τ_y. Data is from 2016, 2017, and 2018, and dollar values in column (6) are in millions of current USD. After-tax income is defined as $Y_{AT} \equiv \left(1 - \frac{\text{Net tax}}{100}\right) Y$, where the net tax rate is defined as $(5) \equiv (1) - (2) - (3) - (4)$.

A.3.2 Estimation of income tax progressivity parameter

To estimate τ_p, we derive the estimation equation from the relationship between after-tax income and pretax income: $Y_{AT} = \lambda Y^{1-\tau_p}$. Taking the log of both sides yields $\log(Y_{AT}) = \log(\lambda) + (1-\tau_p)\log(Y)$. This yields the estimation equation, $\log(Y_{AT}) = \beta_0 + \beta_1 \log(Y)$, where $\beta_1 = 1 - \tau_p$. We therefore regress column (8) from Table A17 on column (7), using population shares for each row as weights (which are implied by percentiles in that row). The results are presented in Table A18; coefficients are significant at the 0.1 percent significance level. The average estimated value for τ_p is 0.177.

Table A18: Income tax progressivity estimation results by year and overall

Coefficient	**2016**	**2017**	**2017**
β_1	0.815 (0.0277)	0.822 (0.0269)	0.833 (0.0231)
β_0	-0.253 (0.0335)	-0.243 (0.0323)	-0.224 (0.0275)
Implied $\hat{\tau}_{p,t}$	0.185	0.178	0.167
Average 2016-2018 $\hat{\tau}_p$	0.177		

Notes: Table A18 reports estimation results. Standard errors in parentheses.

A.4 OECD Statistics

A.4.1 Estimation sample

We use OECD data to apply the consumption tax estimation in equation (5) of Mendoza, Razin, and Tesar (1994) to the 2016-2018 period:

$$\tau_{c,t} \quad = \quad 100 \times \frac{5110_t + 5121_t}{C_t + G_t - GW_t - 5110_t - 5121_t} \tag{14}$$

Specifically, we use values for the United States from three data series (OECD, 2024c,b,a) to populate the 2016, 2017, and 2018 entries of Panels A, B, and C in Table A19.

Table A19: OECD data by year

Variable	Description	2016	2017	2018	Source
Panel A: Total tax revenue (all levels of government)					
5110	General taxes on goods and services	384,762	406,032	427,706	OECD (2024c)
5121	Excises	158,781	161,486	165,392	
Panel B: Final consumption expenditure					
C	Private	12,338,566	12,894,210	13,513,511	OECD (2024b)
G	Government	2,653,374	2,715,714	2,859,732	OECD (2024a)
Panel C: Compensation of employees by source					
GW	Paid by producers of gov't services	1,798,955	1,846,072	1,922,217	OECD (2024a)

Notes: Table A19 reports OECD data used in the consumption tax rate estimation method of Mendoza, Razin, and Tesar (1994). Dollar values are in millions of current USD for that year, rounded to the nearest dollar.

A.4.2 Estimation of consumption tax parameter

We estimate the consumption tax for each year using equation (14) applied to the data in Table A19. The year's estimated consumption tax is reported in its respective column of Table A20. The parameter value for τ_c is the average across years for the 2016-2018 period: 0.043.

Table A20: Consumption tax rate estimation results by year and overall

Variable	Description	2016	2017	2018
$\hat{\tau}_{c,t}$	Annual rate (share)	0.043	0.043	0.043
$\hat{\tau}_c$	Average rate 2016-2018 (share)	0.043		

B Model Appendix

B.1 Value functions

The subjective value of college for $j = 4$ is given by

$$
\begin{aligned}
&\hat{V}(j, h, s, \eta, a, \hat{p}) = \max_{\hat{c} \geq 0, \hat{a}'} U(c, j, h) \qquad (15)\\
&+ \beta\psi_j[\hat{p}E_{\eta'|h,\eta}V(j+1, h, s, \eta', \hat{a}') + (1-\hat{p})E_{\eta'|\ell,\eta}V(j+1, \ell, s, \eta', \hat{a}')]\\
&s.t.\\
&(1+\tau_c)\hat{c} + \hat{a}' + (1-\theta-\theta^{pr})\kappa = y_{j,h,s,\eta,a} + a + Tr_j - T(y_{j,h,s,\eta,a})\\
&\hat{a}' \geq -\bar{A}j[(1-\theta-\theta^{pr})\kappa + \bar{c}]
\end{aligned}
$$

The idiosyncratic state of a consumer while $j > 4$ and $j \neq j_f + j_a$ is given by the tuple (j, e, s, η, a). The consumer's value function is given by

$$
V(j, e, s, \eta, a) = \max_{d_f \in \{0,1\}} (1-d_f)V^R(j, e, s, \eta, a) + d_f V^D(j, e, s, \eta, a) \qquad (16)
$$

where the value of repayment for $j > 4$ and $j \neq j_f + j_a$ is given by

$$
\begin{aligned}
&V^R(j, e, s, \eta, a) = \max_{c \geq 0, a'} U(c, j, e) + \beta\psi_j E_{\eta'|e,\eta}V(j+1, e, s, \eta', a') \qquad (17)\\
&s.t.\\
&(1+\tau_c)c + a' = y_{j,e,s,\eta,a} + a + \mathbb{I}_{\{a<0\}}r_{SL}a + Tr_j - T(y_{j,e,s,\eta,a})\\
&a' \geq \min[(1+r_{SL})a + \rho_R(j, a), 0]
\end{aligned}
$$

Alternatively, the consumer can choose delinquency. If a consumer chooses delinquency, their value function for $j > 4$ and $j \neq j_f + j_a$ is given by

$$
\begin{aligned}
&V^D(j, e, s, \eta, a) = U(c, j, e) - \xi_D + \beta\psi_j E_{\eta'|e,\eta}V(j+1, e, s, \eta', a') \qquad (18)\\
&s.t.\\
&(1+\tau_c)c = y_{j,e,s,\eta,a} + Tr_j - T(y_{j,e,s,\eta,a}) - \rho_D(j, a, y_{j,e,s,\eta,a})\\
&a' = (1+r_{SL})a + \rho_D(j, a, y_{j,e,s,\eta,a}) - \phi_D[\rho_R(j, a) - \rho_D(j, a, y_{j,e,s,\eta,a})]
\end{aligned}
$$

where ξ_D is the stigma cost of delinquency. In the case of delinquency, consumers do not make a consumption-savings decision. Instead, they have their wage garnished to make a partial payment of $\rho_D(j, a, y_{j,e,s,\eta,a})$. Therefore, they consume whatever remains from their disposable income, plus accidental bequests, after making the partial payment on the outstanding student loan. As mentioned in Section 3.3, ϕ_D is the fraction of missed payment (difference between full payment and partial payment) that is charged as a collection fee. The outstanding principal plus interest is then augmented by the missed payment plus the collection fee (net of any partial payment).

When $j = j_f + j_a$ and the consumer chooses delinquency, for simplicity, we assume those consumers cannot make an inter vivos transfer to their child in order. Therefore, the value function for delinquency is largely the same as in equation (18), with the difference that the parent has a term reflecting altruistic utility toward their child, represented by the addition of $\beta_c E_{\eta'|\ell}\hat{W}(s_c, \eta', b = 0, \hat{p})$ to the objective function.

B.2 Definition of equilibrium

To define the equilibrium, we must first discuss notation and define the Social Security transfer function. Let $\overrightarrow{\omega}$ denote the idiosyncratic state of a consumer. This state depends on age and enrollment status in the following way:

$$\overrightarrow{\omega} = \begin{cases} (s, \eta, a, \hat{p}) & \text{for 18-year-olds, before making the college entrance decision} \\ (j, h, s, \eta, a, \hat{p}) & \text{for consumers in college} \\ (j, e, s, \eta, a) & \text{for consumers not enrolled, dropouts, or graduates, if } j \neq j_f + j_a \\ (j, e, s, \eta, a, s_c, \hat{p}) & \text{if } j = j_f + j_a \end{cases} \tag{19}$$

Furthermore, let $\hat{d}_{d,t}(\overrightarrow{\omega})$ and $d_{d,t}(\overrightarrow{\omega})$ denote the dropout decisions that solve the endogenous discrete dropout problems in the continuation values of equations (3) and (4), respectively.

Social Security transfer function: Social Security transfers replace a fraction χ of the average labor earnings for the 30 years before retirement conditional on education and skill plus the average unconditional labor earnings for the 30 years before retirement, divided by two. The transfer function is given by

$$ss_{e,s} = \frac{\chi}{2}\left[\frac{\int w_e \eta \epsilon_{j,e,s} \Omega_t d(\overrightarrow{\omega}|18 \leq j < j_r, e, s)}{\int \Omega_t d(\overrightarrow{\omega}|18 \leq j < j_r, e, s)} + \frac{\int w_e \eta \epsilon_{j,e,s} \Omega_t d(\overrightarrow{\omega}|18 \leq j < j_r)}{\int \Omega_t d(\overrightarrow{\omega}|18 \leq j < j_r)}\right] \tag{20}$$

Definition Given an initial level of capital stock K_0 and an initial distribution over idiosyncratic states $\Omega_0\,(\overrightarrow{\omega})$, a competitive equilibrium consists sequences of household value functions $\{\hat{W}_t(\overrightarrow{\omega}), V_t(\overrightarrow{\omega}), \hat{V}_t(\overrightarrow{\omega}), V_t^R(\overrightarrow{\omega}), V_t^D(\overrightarrow{\omega})\}$, household college entrance and dropout policy functions $\{\hat{d}_{e,t}(\overrightarrow{\omega}), \hat{d}_{d,t}(\overrightarrow{\omega}), d_{d,t}(\overrightarrow{\omega})\}$, household consumption and next period asset policy functions $\{\hat{c}_t(\overrightarrow{\omega}), \hat{a}'_t(\overrightarrow{\omega}),\ c_t(\overrightarrow{\omega}), a'_t(\overrightarrow{\omega})\}$, household delinquency policy functions $\{d_{f,t}(\overrightarrow{\omega})\}$, household inter vivos transfer policy function

$\{b_t(\overrightarrow{\omega})\}$, production plans $\{Y_t, K_t, L_{\ell,t}, L_{h,t}\}$, tax policies $\{\gamma_t\}$, prices $\{r_t, w_{\ell,t}, w_{h,t}\}$, Social Security transfers $\{ss_{t,e,s}\}$, accidental bequests $\{Tr_{t,j}\}$, and measures $\{\Omega_t(\overrightarrow{\omega})\}$ such that:

(i) Given prices, transfers, and policies, the value functions and household policy functions solve the consumer problems in equations (1)-(6) and (15)-(18);
(ii) The saving interest rate and wage rates satisfy equations firm first order conditions;
(iii) Social Security transfers satisfy equation (20);
(iv) Accidental bequests are transferred to households between ages 50 and 60 ($33 \leq j \leq 43$) after deducting expenditure on private education subsidies[25]

$$Tr_{t+1,j} = \frac{\int (1-\psi_j) a'_t(\overrightarrow{\omega}) \Omega_t d(\overrightarrow{\omega}) - \kappa \int \theta^{pr} \mathbb{I}_{e=h \text{ and } j \in \{1,2,3,4\}} \Omega_{t+1} d(\overrightarrow{\omega})}{\sum_{j=33}^{43} N_{t+1,j}} \tag{21}$$

where $N_{t,j}$ denotes the mass of population of age j at time t;
(v) Government budget constraint balances as follows, by adjusting γ:

$$\int [\tau_c c_t(\overrightarrow{\omega}) + T(y_{t,j,e,s,\eta,a})] \Omega_t d(\overrightarrow{\omega}) = G_t + E_t + D_t + SS_t \tag{22}$$

where G_t, E_t, D_t, and SS_t are government consumption, total public education subsidy, federal student loan program expenditure, and Social Security expenditure;
(vi) Labor, capital, and goods markets clear in every period t; and
(vii) $\Omega_{t+1} = \Pi_t\Big(\Omega_t\Big)$, where Π_t is the law of motion that is consistent with consumer household policy functions and the exogenous processes for population, labor productivities, skill, subjective beliefs, and the true probabilities of being allowed to continue college for each skill endowment bin.

B.3 Computational algorithm for the stationary equilibrium

1. Guess interest rate r_{guess}, wage rates $w_{\ell,\text{guess}}$ and $w_{h,\text{guess}}$, the level parameter for the income tax rate γ_{guess}, accidental bequests $Tr_{j,\text{guess}}$, and Social Security transfers $ss_{e,s,\text{guess}}$
2. Use backward induction to solve consumer problem: $j = j_f + j_a + 1, \ldots, J$ (equations (16)-(18))
3. Guess subjective value function before college, $\hat{W}_{\text{guess}}(s, \eta, a, \hat{p})$ (equation (1))
4. Use backward induction to solve consumer problem: $j = 1, \ldots, j_f + j_a$ (equations (1)-(6) and (15))-(18))

[25] In our baseline calibration and in all of the counterfactual exercises, accidental bequests are always positive because the assets of those who die exceed the expenditure on private subsidies to education costs. If they did not exceed private subsidies, then bequests would be negative, which is equivalent to a lump-sum tax.

- In solving the consumer problem at $j = j_f + j_a$, use $\hat{W}_{\text{guess}}(s, \eta, a, \hat{p})$ for altruistic term
- For consumers before college graduation age, not in college, and without loans, $(j \leq 4, e = \ell, a \geq 0)$, and for consumers after college graduation age and without loans, $(j > 4, a \geq 0)$, use golden-section search to solve consumption-savings problem. Continuous optimization is possible as these consumers will not choose delinquency
- For consumers before college graduation age and, in college or with loans $(j \leq 4, e = h$ or $a < 0)$ and, for consumers after college graduation age with loans $(j > 4, a < 0)$, use discrete grid search for optimization as these consumers may choose delinquency

5. Use new value before college to update $\hat{W}_{\text{guess}}(s, \eta, a, \hat{p})$; repeat 4.-5. until convergence
6. Guess initial distribution of 18-year-old consumers $\Omega(j = 1, s, \eta, a, \hat{p})_{\text{guess}}$
7. Simulate and solve for distribution of Ω for $j = 2, \ldots, J$
8. Use distribution of Ω for $j = j_f + j_a$ and inter vivos transfers policy function to compute new estimates for distribution of initial 18-year-old consumers $\Omega(j = 1, s, \eta, a, \hat{p})$
9. Update $\Omega(j = 1, s, \eta, a, \hat{p})_{\text{guess}}$ and repeat 7.-9. until convergence
10. Given the stationary distribution of Ω for $j = 1, \ldots, J$, solve for new guesses:
    - Compute interest and wage rates from the firm's first order conditions
    - Compute the level parameter for the income tax rate using the government budget constraint (equation (22))
    - Compute accidental bequests and Social Security transfers (equations (21) and (20))
11. Update guesses in 1., and repeat steps 2.-11. until convergence

Solving for the transition path is analogous, except there are time subscripts for all value functions, policy functions, prices, taxes, transfers, and distributions.

B.4 Measuring welfare

Let value functions with a tilde denote expected lifetime utilities computed by the planner. For $j = j_f + j_a + 1, \ldots, J$, the values computed by the planner are equal to that of the consumer (i.e., $\tilde{V}(\vec{\omega}) = V(\vec{\omega})$). They are equal because subjective beliefs about being allowed to continue in college only affects the college enrollment decision, the inter vivos transfer decision, and the decisions leading up to and including the age at which the inter vivos transfer decision is made $(j_f + j_a)$. For $j = j_f + j_a$, the age at which the consumer makes the inter vivos transfer decision, the planner's value function is given by

$$\tilde{V}(j,e,s,\eta,a) = \sum_{s_c} \pi_{s_c}(s_c) \sum_{\hat{p}} \pi_{\hat{p}}(\hat{p}|s_c)[(1-d_f)\tilde{V}^R(j,e,s,\eta,a,x,s_c,\hat{p}) \tag{23}$$
$$+ d_f \tilde{V}^D(j,e,s,\eta,a,s_c,\hat{p})]$$

In computing $\tilde{V}(\cdot)$, the planner takes as given the delinquency decision $d_f(\cdot)$, which solves equation (5). The values for $\tilde{V}^R(\cdot)$ and $\tilde{V}^D(\cdot)$ are given by

$$\tilde{V}^R(j,e,s,\eta,a,s_c,\hat{p}) = U(c,j,e) + \beta\psi_j E_{\eta'|e,\eta}\tilde{V}(j+1,e,s,\eta',a') + \beta_c E_{\eta'|\ell}\tilde{W}(s_c,\eta',b,\hat{p})$$
$$\tilde{V}^D(j,e,e,\eta,a,s,s_c,\hat{p}) = U(c,j,e) - \xi_D + \beta\psi_j E_{\eta'|e,\eta}\tilde{V}(j+1,e,s,\eta',a') + \beta_c E_{\eta'|l}\tilde{W}(s_c,\eta',b,\hat{p})$$

where $\tilde{W}(\cdot)$ is the value before college computed by the planner (given below) and policy functions $\{c(\cdot), a'(\cdot), b(\cdot)\}$, taken as given, solve equation (6) and the parent's delinquency value function at age $j = j_f + j_a$. These value functions are the first of the two instances in which the planner's computation differs from that of the consumer with subjective beliefs. Note that the planner uses $\tilde{W}(\cdot)$, whereas the consumer with subjective beliefs uses $\hat{W}(\cdot)$. For $j = 5, \ldots, j_f + j_a - 1$, the planner's value function is computed analogously. For $j = 4$, the planner's value of college is given by

$$\tilde{V}(j,h,s,\eta,a,\hat{p}) = U(c,j,h) \tag{24}$$
$$+ \beta\psi_j[p(s)E_{\eta'|h,\eta}\tilde{V}(j+1,h,s,\eta',a') + (1-p(s))E_{\eta'|\ell,\eta}\tilde{V}(j+1,\ell,s,\eta',a')]$$

The planner's value of college for $j = 1,2,3$ and the planner's value of not going to college (as well as the value of dropping out) for $j \leq 4$ are computed analogously. Finally, the planner's value before college is given by

$$\tilde{W}(s,\eta,a,\hat{p}) = q(s)[(1-\hat{d}_e)\tilde{V}(1,\ell,s,\eta,a) + \hat{d}_e\tilde{V}(1,h,s,\eta,a,\hat{p})] \tag{25}$$
$$+ (1-q(s))\tilde{V}(1,\ell,s,\eta,a)$$

where the planner takes as given the enrollment decision $\hat{d}_e(\cdot)$, which solves equation (1). This value function is the second of the two instances in which the planner's computation differs from that of the consumer with subjective beliefs. The planner uses $\tilde{V}(\cdot)$, which uses the true probability $p(s)$ for the likelihood of being allowed to continue college, whereas the consumer with subjective beliefs uses $\hat{V}(\cdot)$, which uses the subjective belief probability $\hat{p}$ for the likelihood of being allowed to continue in college.

To measure welfare changes for the 18-year-old consumer, we use two statistics: (1) the share of the population that is strictly worse/better off and (2) consumption-equivalent variation. Following Abbott, Gallipoli, Meghir, and Violante (2019), we measure consumption equivalence units relative to the value of not going to college in the initial stationary equilibrium. We do this because the value of not going to college does not include any utility fixed costs. For the average 18-year-old in period t of the transition to the new stationary steady state, the consumption equivalent variation, $g_{c,t}$, is computed using the following equation

$$(1+g_{c,t})^{1-\sigma}\int \tilde{V}_{\text{initial}}(1,\ell,s,\eta,a,\hat{p})\Omega_{\text{initial}}d(\overrightarrow{\omega}) = \int \tilde{W}_t(s,\eta,a)\Omega_t d(\overrightarrow{\omega}) \tag{26}$$

where on the left-hand side of the equation, "initial" refers to the initial stationary equilibrium. To compute the resulting gains or losses from a policy change in consumption equivalent units, we report the difference between period t and the initial stationary equilibrium: $100 \times (g_{c,t} - g_{c,\text{initial}})$. When measuring welfare holding the distribution of 18-year-old consumers fixed to that from the initial stationary equilibrium, we use distribution Ω_{initial} instead of Ω_{t} for the right-hand side of equation (26). This measure has the property that positive values indicate gains and negative values indicate losses.

C Model Validation Appendix

College wage premiums by skill Table A21 reports the college wage premium by skill tercile in the data and the baseline model. Data moments are from the NLSY97, as reported in Table A10 of Appendix A.1.3. The college wage premium in the model is the median earnings for an individual with a four-year college degree divided by the median earnings for an individual without a four year college degree for workers in the age group from 25 to 39 given their skill level (ages are chosen to match the NLSY97 sample). While the wage premium for the middle skill tercile was targeted in our calibration, the model does well in explaining college wage premiums for all skill endowment bins. Specifically, the college wage premium is increasing in skill. As indicated by the enrollment rates reported in Table 11, the enrollment rate is increasing in skill in the baseline equilibrium, implying that the marginal returns to college are lower than the average returns.[26]

Subjective beliefs by enrollment status and skill Table A22 reports subjective beliefs in the baseline calibration by enrollment status and skill bin. The difference between the reported mean expectations about BA attainment and the realized graduation rate in the model matches that ob-

[26] Alternatively, note that in the main text we perform a quasi-experimental study in our baseline calibration in which we increase the tuition subsidy by 1,000 dollars. In this exercise, we observe a decline in the average college wage premium, which also indicates that the marginal returns to college are lower than the average returns in the baseline initial economy.

Table A21: College wage premiums by skill endowment tercile

Skill	**Data**	**Model**
Low	1.35	1.34
Medium	*1.38*	*1.38*
High	1.47	1.43

Notes: Table A21 reports the college wage premium in the NLSY97 and in the baseline model by skill.

served in the data (from Tables 3 and 4) although these moments were not directly targeted in the calibration.

Table A22: Subjective beliefs by enrollment status and skill endowment

		Model			**Data**
	Skill	(a) **Expected graduation prob.**	(b) **Realized graduation rate**	**Difference** $(a)-(b)$	**Difference** $(a)-(b)$
Panel A: Enrollees	Low	80.29	44.00	36.28	36.69
	Medium	85.46	58.40	27.06	28.58
	High	90.50	77.10	13.40	14.78
Panel A: Non-enrollees	Low	66.07	44.00	22.07	21.42
	Medium	71.87	58.40	13.47	8.06
	High	77.19	77.10	0.09	-4.47

Notes: Table A22 reports subjective beliefs about college graduation likelihood by skill endowment bin from the model survey on expectations about BA attainment by enrollment status and skill bin, along with the realized graduation rate of the skill bin for those who enroll in college. The difference refers to the difference between the reported mean expectations and the realized graduation rate. The estimated differences in the NLSY97 data are also included for comparison (see Tables 3 and 4). Expectations, graduation rates, and differences are all in units of percentages.

Student loan incidence by persistence status Table A23 reports loan uptake by persistence status for a given cohort of enrollees in the data (Panel A, from Table 5 in Section 2.2), in the model baseline (Panel B), and in a partial equilibrium counterfactual in which we shut off subjective beliefs by setting $\hat{p} = p(s)$ for all s but do not allow general equilibrium objects to adjust (Panel C). These data moments are untargeted in our calibration. The baseline model does reasonably well in accounting for the magnitude of loan balances among student debtors by persistence status in columns (4) and (5). However, the model does not perform well in matching the share of aggregate balances in column (2) and the share of non-persisters with any student debt in column (3). We attribute this to fewer dropouts with small loan balances in the model as compared to the data. A comparison of Panels B and C in Table A23 indicates that student loan statistics by persistence status barely change when beliefs are corrected. These statistics indicate that subjective beliefs do not affect borrowing behavior conditional on enrollment in college.

Despite the similarity in loan statistics across Panels B and C in Table A23, one should not infer that the intrinsic riskiness of college as an investment is the sole driver of total debt held by dropouts in our baseline model, with subjective beliefs playing no role. In fact, although enrollment statistics are not shown in Table A23, when beliefs are corrected (Panel C), in comparison to the baseline (Panel B), the total mass of enrollees decreases leading to a fall in the total mass of dropouts. Consequently, as Table A24 shows, both the total mass of dropouts with a student loan and the total amount of debt held by dropouts decreases by 19 percent.

Table A23: Student loans by persistence status

Panel and Source	Persistence status	(1) % of enrollees	(2) % of SL $	(3) % with SL	(4) Average $	(5) Median $
A: Data	Did not persist	24	19	77	10,795	9,500
	Persisted	76	81	64	17,250	18,499
B: Baseline	Did not persist	19	3	23	6,293	6,168
	Persisted	81	97	76	12,884	12,336
C: Baseline, corrected beliefs	Did not persist	19	3	19	6,342	6,168
	Persisted	81	97	76	12,892	12,336

Notes: Table A23 reports loan uptake patterns by persistence status to the third academic year for a given cohort of enrollees. Panels A, B, and C contain moments from the HSLS:09, as reported in Table 5, the model baseline equilibrium, and when $\hat{p} = p_c$, so that consumers have correct beliefs, but general equilibrium objects are not allowed to adjust.

Table A24: Changes in student loan uptake among dropouts with corrected beliefs

Variable	% changes from baseline
Total dropout debtors	-19
Total dropout debt	-19

Notes: Table A24 reports the change in total loan uptake for a given cohort of 18-year-olds when $\hat{p} = p_c$, so that consumers have correct beliefs, but general equilibrium objects are not allowed to adjust.

D Main Experiment: Federal Loan Limit Expansion Appendix

D.1 Equivalence of worse off and non-enrollment to over-enrollment

Proposition. *In a partial equilibrium economy without parental altruism, transitioning from non-enrollee to an over-enrolled college student is both sufficient and necessary to suffer welfare losses after the loan limit expansion.*

Proof. Let $\hat{V}_{0,h}$, $V_{0,h}$, $\hat{V}_{0,\ell}$, and , $V_{0,\ell}$ denote, in the status quo economy, the subjective value of college, the value of college with correct beliefs, the subjective value of not going to college, and the value of not going to college with correct beliefs, respectively. Let $\hat{V}_{1,h}$, $V_{1,h}$, $\hat{V}_{1,\ell}$, and , $V_{1,\ell}$ denote the analogous values in an economy with a higher federal student loan limit (post-policy economy).

Suppose individuals are optimistic about graduation such that $\hat{V}_{0,h} > V_{0,h}$ and $\hat{V}_{1,h} > V_{1,h}$. Without an altruistic motive to make a transfer to a child in the future, $\hat{V}_{0,\ell} = V_{0,\ell}$ and $\hat{V}_{1,\ell} = V_{1,\ell}$ because subjective beliefs do not affect the value of not going to college. Furthermore, in partial equilibrium without an altruistic motive to make transfers to future children, $V_{0,\ell} = V_{1,\ell}$.

For an 18-year-old that chooses non-enrollment in the status quo economy, it must be that $\hat{V}_{0,h} < \hat{V}_{0,\ell}$. Their realized value is $V_{0,\ell}$.

If this individual chooses non-enrollment in the post-policy economy, they do not experience a welfare gain or loss because the post-policy realized value is $V_{0,\ell} = V_{1,\ell}$.

If this individual chooses enrollment in the post-policy economy, it must be that $\hat{V}_{1,h} > \hat{V}_{1,\ell}$. The realized value in the post-policy economy for this individual is $V_{1,h}$. This individual is over-enrolled if $V_{1,h} < V_{1,\ell}$. This individual is strictly worse off if $V_{1,h} < V_{0,\ell}$. Because $V_{0,\ell} = V_{1,\ell}$ in a partial equilibrium without altruism, the criteria for being strictly worse off and for being an over-enrollee are the same.

Furthermore, it is straightforward to establish that an individual that enrolls in the pre-policy economy is never strictly worse off with a limit expansion. Therefore, a non-enrollee in the status quo economy becoming an over-enrolleed college student in the post-policy economy is both a sufficient and necessary condition for being strictly worse off.

D.2 Subjective and realized values of high school and college

Table A25 reports the subjective and realized average values of high school and college for a specifically identified group of consumers under three values of the federal student loan limit in partial equilibrium. Consequently, the only factor that can lead to changes in values of high school and college across the three scenarios is the limit change. The specific group is identified as 18-year-olds who, given the option to enroll, would go from non-enrollment in the initial stationary equilibrium to over-enrollment when the limit expands to $\bar{A} = 0.56$. For this group, we compare values for two limit expansions, $\bar{A} = 0.56$ (Panel A) and $\bar{A} = 1$ (Panel B) to values for high school and college in the initial equilibrium when $\bar{A} = 0.37$. For each panel, values in the initial equilibrium are in columns labeled "Initial"; values after the expansion are in columns labeled "Final". By construction of the sample in this table, in the "Final" columns of Panel A the average subjective value of college is higher than the value of high school, whereas the average realized value of college is less than the value of high school. For the same population, the average realized value of college increases by a higher amount for a large limit expansion ($\bar{A} = 1$) in comparison to a moderate limit expansion. This larger increase in the realized value of college is the reason this population would no longer be over-enrolled for a large limit expansion. To see this, compare rows "Realized" in Panels A and B under column "College" in "Final-Initial".

Table A25: Values of high school and college

Population: Inflow from non-enrollment to over-enrollment ($\bar{\mathbf{A}}_{\text{initial}}$ to $\bar{\mathbf{A}} = 0.56$) | Option to enroll						
	Initial		**Final**		**Final - Initial**	
Subjective/Realized	**High school**	**College**	**High school**	**College**	**High school**	**College**
Panel A: $\bar{\mathbf{A}}_{\text{initial}}$ to $\bar{\mathbf{A}} = 0.56$						
Subjective	-88.66	-94.06	-88.55	-85.59	0.11	8.47
Realized	-88.74	-94.99	-88.67	-90.14	0.07	4.85
Panel B: $\bar{\mathbf{A}}_{\text{initial}}$ to $\bar{\mathbf{A}} = 1$						
Subjective	-88.66	-94.06	-88.39	-78.37	0.27	15.69
Realized	-88.74	-94.99	-88.52	-84.59	0.22	10.40

Notes: Table A25 reports the subjective and realized average values of high school and college for a specifically identified group of consumers under three values of the federal student loan limit. The specifically identified group includes 18-year-olds who, given the option to enroll, would go from non-enrollment in the initial stationary equilibrium to over-enrollment when the limit expands to $\bar{A} = 0.56$. The three values of limit are $\bar{A} = 0.37$ (the initial equilibrium), $\bar{A} = 0.56$, and $\bar{A} = 1$. The analyses presented in this table are from a partial equilibrium exercise in which the income tax rate, prices, bequests, Social Security transfers, and the 18-year-old distribution are fixed at their initial steady state values. In the table, the labels "Subjective" and "Realized" refer to the subjective value of high school/college computed based on subjective beliefs and the realized value of high school/college computed based on correct beliefs, respectively; the labels "Initial" and "Final" refer to the status quo limit and the limit after an expansion ($\bar{A} = 0.56$ or $\bar{A} = 1$), respectively.

D.3 Moderate limit expansion ($\bar{\mathbf{A}} = 0.56$): additional results

D.3.1 Consumption-equivalent variation for 18-year-olds by key characteristics

In Sections 6.2 and 6.3, we analyzed the welfare implications of a moderate limit expansion from the status quo to $\bar{A} = 0.56$. In those sections, we reported the welfare changes by groupings of those strictly worse off and better off given skill and initial characteristics of each grouping. Conversely, in this section, we report welfare changes by splitting 18-year-olds by characteristics such as skill, initial AR(1) productivity, parental income tercile, and expectations about BA attainment. In partial equilibrium, the group that experiences the largest welfare losses are low-skilled consumers from poor families with low AR(1) productivity and high expectations about BA attainment likelihood. The losses experienced by this group amounts to 0.79 percent of lifetime consumption. In general equilibrium, across steady states, the average losses for this group are essentially overturned. Furthermore, in general equilibrium additional losses arise which are especially notable for those with high skill, from rich families, and with high expectations about BA attainment. This is the group that is most likely to enroll in college and become a highly educated worker in the baseline economy and the new steady state, and they are hurt by the decline in the wage rate for workers with a college degree.

Table A26: Consumption-equivalent variation for 18-year-olds ($\bar{A}_{\text{initial}}$ to $\bar{A} = 0.56$)

			(I) Partial equilibrium			(II) General equilibrium		
			Skill			Skill		
Persistent earnings	**Parental inc. tercile**	**Exp. prob. BA**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
Low (0 to 20th percentile)	1	*0 to 39*	0.08	0.08	0.08	1.16	1.16	1.16
		40 to 79	0.05	0.07	2.46	1.13	1.00	2.62
		80 to 100	-0.79	0.47	4.19	0.07	0.69	2.75
	2	*0 to 39*	0.08	0.09	0.12	1.11	1.06	1.02
		40 to 79	0.20	0.67	2.16	0.97	1.01	1.06
		80 to 100	0.42	1.39	2.35	0.90	0.90	0.39
	3	*0 to 39*	0.09	0.10	0.15	0.94	0.71	0.25
		40 to 79	0.15	0.27	0.46	0.82	0.49	-0.34
		80 to 100	0.16	0.25	0.40	0.80	0.43	-0.39
Medium (20th to 80th percentile)	1	*0 to 39*	0.09	0.09	0.09	1.19	1.19	1.19
		40 to 79	-0.03	1.21	4.35	1.08	1.74	4.01
		80 to 100	0.05	1.73	3.73	0.84	1.99	2.55
	2	*0 to 39*	0.11	0.13	0.27	1.15	1.15	1.27
		40 to 79	0.17	0.88	1.89	1.00	1.13	0.58
		80 to 100	0.37	0.87	1.41	0.88	0.55	-0.27
	3	*0 to 39*	0.12	0.14	0.30	0.98	0.86	0.24
		40 to 79	0.14	0.22	0.33	0.85	0.48	-0.41
		80 to 100	0.14	0.20	0.29	0.82	0.43	-0.45
High (80th to 100th percentile)	1	*0 to 39*	0.14	1.25	2.35	1.23	1.54	3.04
		40 to 79	0.64	1.18	1.96	1.46	1.70	1.65
		80 to 100	0.71	1.07	1.69	1.52	1.46	0.96
	2	*0 to 39*	0.21	0.99	2.00	1.22	1.48	2.56
		40 to 79	0.41	0.66	0.85	1.19	1.00	0.00
		80 to 100	0.31	0.43	0.67	0.97	0.49	-0.37
	3	*0 to 39*	0.15	0.27	1.13	1.06	0.93	0.78
		40 to 79	0.13	0.16	0.19	0.90	0.53	-0.33
		80 to 100	0.12	0.14	0.18	0.88	0.50	-0.36

Notes: Table A26 reports consumption-equivalent variation estimates in percentage points after a federal loan limit expansion from $\bar{A}_{\text{initial}}$ to $\bar{A} = 0.56$ for 18-year-olds by AR(1) productivity, skill, parental income, and subjective beliefs of BA attainment likelihood in the baseline in partial and general equilibrium. In partial equilibrium, the income tax rate, prices, bequests, Social Security transfers, and the 18-year-old distribution are fixed at their initial steady state values. In general equilibrium, the aforementioned objects are allowed to adjust, and we compare the initial steady state value to the corresponding final steady state value in each skill, parental income, and subjective beliefs bin.

D.3.2 General equilibrium adjustments

The effects of expanding the federal loan limit to $\bar{A} = 0.56$ on the baseline model's steady state equilibrium are shown in Table A27. The effects on the model economy are summarized by changes in education and skill statistics (Panel A), macroeconomic aggregates (Panel B), and prices, income tax rate, and transfers (Panel C).

The first row of Panel A reports changes in the enrollment rate by skill. The expansion in the federal loan limit increases enrollment for all skill endowment bins. Enrollment increases because young adults previously constrained in their access to federal credit can now access more of it.

Table A27: Steady state changes ($\bar{A}_{\text{initial}}$ to $\bar{A} = 0.56$)

Panel	Variable	Changes from initial equilibrium
A: Education and skill statistics	College enrollment rate by s	(5.73,6.87,6.22)
Units: percentage point change	Graduation rate	-0.45
	Population share college graduates	3.89
	Over-enrollment	(4.10,1.55,-0.48)
B: Macroeconomic aggregates	Low-education labor (efficiency units)	-5.62
Units: percentage point/percentage change	High-education labor (efficiency units)	10.85
	Labor	1.43
	Capital	0.62
	Output	1.14
	Consumption	0.98
C: Prices, income tax rate, transfers	Risk-free savings interest rate	0.06
Units: percentage point/percentage change	Wage rate for low-education	1.16
	Wage rate for high-education	-2.04
	Income tax rate | Baseline mean income	-0.07
	Inter vivos transfers	-10.47
	Accidental bequests	1.58
	$\text{ss}_{\ell,s}$ by s	(1.32,1.37,1.49)
	$\text{ss}_{h,s}$ by s	(-0.48,-0.67,-0.71)

Notes: Table A27 provides results from a steady state comparison after a federal loan limit expansion from $\bar{A}_{\text{initial}}$ to $\bar{A} = 0.56$ in the baseline model. Panels A, B, and C report changes in education and skill statistics, macroeconomic aggregates, and prices, income tax rate, and transfers, respectively. Statistics that vary over s are presented as a tuple in the order (s_1, s_2, s_3).

The next row of Panel A indicates that the expansion in enrollment leads to a lower graduation rate overall. This is because the average college student now has lower skill and is therefore less likely to graduate. Nevertheless, higher enrollment also increases the share of college graduates in the population. The final row of Panel A shows that over-enrollment increases for the low- and medium-skill, but decreases for the high-skill. See Section 6.1 for a discussion on how a limit expansion can increase or decrease over-enrollment.

Moving to Panel B, the increase in the mass of college graduates increases the total efficiency units of high-education labor, which outweighs the fall in the total efficiency units of low-skill labor, leading to an increase in aggregate labor. Aggregate capital increases because the new equilibrium features a higher share of college graduates. The increase in aggregate labor and capital lead to an increase in output and consumption.

In Panel C, the risk-free interest rate on savings rises because aggregate labor increases more than the aggregate capital. With fewer low-education workers and more high-education workers, the wage rate for low-education workers increases and the wage rate for high-education workers decreases. The average income tax rate decreases slightly because the economy has more college graduates, who pay higher marginal tax rates. Inter vivos transfers decline because parents realize that their children can use more student loans to pay for college. Accidental bequests rise because, on average, consumers have more assets. The signs of Social Security transfers reflect the signs of the wage rate of the respective education groups: the transfers increase for low-education retirees and fall for high-education retirees.

D.3.3 Isolating general equilibrium adjustments on welfare

In Table A28, we isolate the impact of general equilibrium objects on the population that is strictly worse off from a limit expansion to $\bar{A} = 0.56$ in the baseline model. The table establishes that the rise in the wage rate for low-education workers is the primary reason fewer low- and medium-skilled 18-year-olds are worse off in general equilibrium in comparison to partial equilibrium. Furthermore, the decline in the wage rate for high-education workers is the primary driver of welfare losses for the high-skill.

Table A28: 18-year-olds strictly worse off ($\bar{A}_{\text{initial}}$ to $\bar{A} = 0.56$)

		Skill		
Equilibrium	**Total**	**Low**	**Medium**	**High**
Partial	5	12	4	0
General	8	4	0	20
$w_{t,\ell} = w_{initial,\ell}$	19	11	21	26
$w_{t,h} = w_{initial,h}$	1	2	0	0
$r_t = r_{initial}$	9	4	0	22
$\gamma_t = \gamma_{initial}$	9	4	1	22
$Tr_{j,t} = Tr_{j,initial}$	8	4	0	21
$ss_{e,s,t} = ss_{e,s,initial}$	8	4	0	20

Notes: Table A28 reports the share of 18-year-olds that are strictly worse off in total and by skill in the baseline after a federal loan limit expansion from $\bar{A}_{\text{initial}}$ to $\bar{A} = 0.56$ in the following cases: partial equilibrium where all general equilibrium objects are held fixed (that is, income tax rate, prices, bequests, Social Security transfers, and the 18-year-old distribution are fixed at their initial steady state values); general equilibrium; wage rate for low-education workers, $w_{t,\ell}$, fixed at its initial level; wage rate for high-education workers, $w_{t,h}$, fixed at its initial level; risk-free savings rate, r_t fixed at its initial level; income tax level parameter, γ_t, fixed at its initial level; accidental bequests, $Tr_{j,t}$, fixed at its initial level; and Social Security transfers, $ss_{e,s,t}$, fixed at their initial level. For each partial equilibrium case in which an individual general equilibrium object is held fixed, while the relevant variable is fixed at its initial level, the other variables change as they do in general equilibrium.

D.3.4 Welfare implications along the transition path

Figure 6 plots consumption-variation estimates in each period of the transition for 18-year-old consumers from the lowest parental income tercile with low AR(1) productivity (0-20th percentile), high expectations about BA attainment (80-100 percent), and have either low or high skill. When we compute transition dynamics, we assume that the economy is in its steady state in period 0. In period 1, the transition is announced unexpectedly, but there is perfect foresight thereafter. The two consumer groupings are the ones who to stand to be most affected from a limit expansion. For the low-skill group, losses observed in the initial periods of the transition are dampened as the economy converges to the new steady state. This pattern highlights the general equilibrium effect on welfare for this group: in partial equilibrium, the welfare losses for this group amount to 0.79 percent of lifetime consumption (Table A26); once general equilibrium adjustments take place, in the early periods of the transition, the losses are reduced by nearly half, and in the new steady state, the losses are essentially overturned. For the high-skill group, welfare estimates do not change drastically from their values in the first few periods of the transition path as the economy transitions to the new steady state.

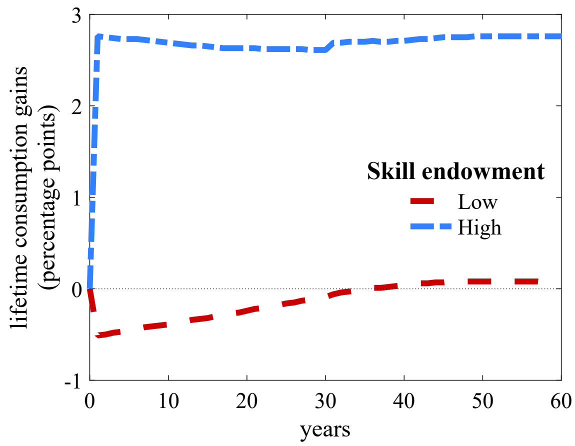


Figure 6: Consumption-equivalent variation ($\bar{A}_{\text{initial}}$ to $\bar{A} = 0.56$)

Notes: Figure 6 plots consumption-equivalent variation estimates in percentage points for 18-year-old consumers with low or high skill who are from the lowest parental income tercile, highest expectations about BA attainment probability (80 to 100), and have low AR(1) productivity (0-20th percentile), in each period of the transition path in general equilibrium.

D.4 Sensitivity analyses

In Section 6, we showed that a moderate expansion in limits could make low- and medium-skill 18-year-olds worse off due to optimism about the likelihood of college graduation. In this section, we perform the same experiment under alternative specifications of our baseline model. In each case, the alternative model specification is re-calibrated to target the same set of moments as the baseline calibration to the extent possible. The share of 18-year-olds worse off in total and by skill are reported in Table A29, and the magnitude of the losses for those worse off by skill are reported in Table A30.

No learning about subjective beliefs In the baseline model, we assumed that consumers update their beliefs to the truth immediately after enrollment as it minimizes the impact of subjective beliefs on consumer behavior. In this sensitivity analysis, we consider the case in which students never learn their true probabilities of being allowed to continue in college and continue to maintain their subjective beliefs for the whole duration of college. A comparison of the baseline with this alternative model specification in Table A29 shows that a slightly higher share of low-skill 18-year-olds are worse off in partial equilibrium; Table A30 shows that the conditional magnitude of losses for the low skill who are worse off is larger.

No endogenous dropout In the baseline model, in addition to the possibility of exogenous dropout, we allowed consumers to drop out endogenously. With enrollees updating their subjective beliefs after enrollment, the choice to drop out allowed the over-enrolled to leave college after the first year if it were the optimal thing to do. In this sensitivity analysis, we do not allow for endogenous dropout. Table A29 shows that a slightly higher share of low-skill 18-year-olds are worse off in partial equilibrium; Table A30 shows that the conditional magnitude of losses for the low skill who are worse off is the same.

Higher add-on for federal student loans In the baseline model, we abstracted from unsubsidized loans and loan fees, which meant the baseline model underestimated the cost of borrowing from the federal student loan program. In this sensitivity analysis, we consider the case in which students pay a higher add-on to the federal student loan interest rate by increasing τ_{SL} from 0.0205 to 0.0305. Tables A29 and A30 show that the welfare implications do not change much in this case as well. The small impact of raising the add-on to federal student loan interest rates suggests that, in the baseline specification, students are not highly responsive to small changes in the cost of borrowing.

College tuition that depends on skill In our baseline calibration, college tuition κ does not depend on skill. In reality, high-skill students are more likely to attend higher quality colleges that cost more. In this sensitivity analysis, we consider the case where college tuition κ depends on skill. We use average tuition estimates by skill reported in Table A13 as target moments. Tables A29 and A30 show that the key welfare insights from the main experiment do not change.

Skill depends on parental education In our baseline calibration, the child's skill does not depend on parental education; our estimates presented in Table A13 indicate that high education parents are more likely to have children with higher skill. In this sensitivity analysis, we consider the case where the child's skill depends on parental education. Tables A29 and A30 show that the key takeaways from the main experiments do not change.

Lower substitutability between low- and high-education labor In this sensitive to analysis, we allow for lower substitutability between low- and high-education labor in comparison to the estimate used in the baseline. We consider setting $\iota = 1 - \frac{1}{3.32} = 0.70$, where 3.32 is the elasticity of substitution and represents the average of the estimate of Goldin and Katz (2007) and the midpoint of the range of 4 to 6 reported in Card and Lemieux (2001); this average is the value used for the analogous parameter to ι in Abbott et al. (2019). The key insights about welfare from the main experiment do not change.

Table A29: Share of 18-year-olds strictly worse off ($\bar{A}_{\text{initial}}$ to $\bar{A} = 0.56$)

		(I) Subjective beliefs				(II) No subjective beliefs			
			Skill				Skill		
Model specification and equilibrium concept		**Total**	**Low**	**Med**	**High**	**Total**	**Low**	**Med**	**High**
Baseline:	Partial	5	12	4	0	0	0	0	0
	General	8	4	0	20	7	0	0	21
No learning:	Partial	6	14	4	0	0	0	0	0
	General	9	6	2	21	7	0	0	21
No endogenous dropout:	Partial	6	15	4	0	0	0	0	0
	General	8	5	0	19	7	0	0	21
Higher add-on:	Partial	6	12	4	0	0	0	0	0
	General	9	5	1	22	7	0	0	22
Tuition & grant | Skill:	Partial	4	9	3	0	0	0	0	0
	General	8	3	2	20	7	0	0	20
Skill | Parental education:	Partial	8	15	8	0	0	0	0	0
	General	11	2	2	26	9	0	0	23
Lower substitutability in	Partial	5	12	4	0	0	0	0	0
low- & high-education labor:	General	8	1	0	23	7	0	0	22
Higher (perfect) substitutability in	Partial	4	10	3	0	0	0	0	0
low- & high-education labor:	General	3	9	0	0	0	0	0	0

Notes: Table A29 reports the share of 18-year-olds that are strictly worse off in total and by skill after a federal loan limit expansion from $\bar{A}_{\text{initial}}$ to $\bar{A} = 0.56$ in the model with subjective beliefs and in an alternative without subjective beliefs. “Partial" refers to a partial equilibrium exercise in which the income tax rate, prices, bequests, Social Security transfers, and the 18-year-old distribution are fixed at their initial steady state values. “General" refers to general equilibrium. For the welfare comparison in general equilibrium, the final steady state distribution of 18-year-olds was used. Welfare is reported for the following cases: baseline, students do not update subjective beliefs for the whole duration of college, no endogenous dropout, higher add-on for the federal student loan interest rate, college tuition and grant depends on skill, child skill depends on parental education, lower substitutability between low- and high-education labor, and higher (perfect) substitutability between low- and high-education labor. Each alternative model specification is re-calibrated.

Higher (perfect) substitutability between low- and high-education labor In this sensitivity analysis, we allow for perfect substitutability between low- and high-education labor. In partial equilibrium, the key insights about welfare from the main experiment do not change: a limit expansion makes some low- and medium-skilled 18-year-olds worse off. In general equilibrium, however, the takeaway is different. General equilibrium effects do not dampen losses for the low-skill as much as they do in the other specifications. This is because, in the other specifications, in general equilibrium, the wage rate for the low-education worker increases benefiting the low-skill. That effect is absent in this alternative model specification because low- and high-education labor is perfectly substitutable and the wage rate declines (due to an increase in aggregate labor efficiency units).

Table A30: Consumption-equivalent variation: 18-year-olds strictly worse off ($\bar{A}_{\text{initial}}$ to $\bar{A} = 0.56$)

	Partial equilibrium			General equilibrium		
	Skill			Skill		
Model specification	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
Baseline	-0.73	-0.20	n/a	-0.16	-2.97†	-0.23
No learning	-0.93	-0.58	-0.02†	-0.35	-0.14	-0.25
No endogenous dropout	-0.73	-0.29	n/a	-0.23	-2.47†	-0.15
Higher add-on	-0.74	-0.24	n/a	-0.21	-0.12	-0.28
Tuition and grant ǀ Skill	-0.47	-0.72	-0.57†	-0.21	-0.41	-0.51
Skill ǀ Parental education	-1.03	-0.45	n/a	-0.07	-0.15	-0.14
Lower substitutability between low- and high-education labor	-0.73	-0.20	n/a	-0.10	-3.81†	-0.40
Higher (perfect) substitutability between low- and high-education labor	-1.04	-0.12	n/a	-0.58	-4.32†	-12.00†

Notes: Table A30 reports consumption-equivalent variation estimates in units of percentage points in the model with subjective beliefs when there is an expansion in the limit from $\bar{A}_{\text{initial}}$ to $\bar{A} = 0.56$ for the 18-year-olds who are strictly worse off in the following cases: baseline, students do not update subjective beliefs for the whole duration of college, no endogenous dropout, higher add-on for the federal student loan interest rate, college tuition and grant depends on skill, child skill depends on parental education, lower substitutability between low- and high-education labor, and higher (perfect) substitutability between low- and high-education labor. “Partial equilibrium" refers to a partial equilibrium exercise in which the income tax rate, prices, bequests, Social Security transfers, and the 18-year-old distribution are fixed at their initial steady state values. To compute welfare, we compare the initial steady state value to the corresponding final steady state value; for the welfare comparison in general equilibrium, the final steady state distribution of 18-year-olds was used. Each alternative model specification is re-calibrated. "n/a" refers to cases in which no one is strictly worse off in a given cell; "†" refers to cases in which almost no one is strictly worse off, but the share is not exactly 0 in a given cell.

E Additional Experiment: Limit Contraction

In our main experiment, we analyzed an expansion in the federal student loan limit. The key mechanism highlighted in the main experiment is that some 18-year-olds may be made worse off because they would transition from non-enrollment in the initial equilibrium to over-enrollment after the limit expansion. The extent to which this transition would happen depends on the extent of optimism about the likelihood of graduation. The optimism about the likelihood of graduation depends on both subjective beliefs about continuning in college and the true likelihood of continuing in college. In the model parameterization of the main text, the former was disciplined with data from the NLSY97, whereas for the latter we assumed that the exogenous skill-specific likelihood of being allowed to continue in college, $p(s)$, is the same for non-enrollees as the one observed for enrollees in the data. Note that, to the extent this imputation implies an upper bound for the true likelihood of continuing, the imputation is not a concern regarding the extent of optimism. In this section, we provide an additional experiment in which the federal student loan limit is reduced, and show that such a limit contraction can make 18-year-olds better off because it transitions them from over-enrollment to non-enrollment (the analogous of the highlighted effects of a limit expansion). For this transition, the imputation of the true likelihood of continuing for non-enrollees does not matter in the sense that the benefits are realized for those who are enrolled in the status quo. For this population, we observe the likelihood of continuing college in the data.

Table A31: Share of 18-year-olds strictly better off ($\bar{A}_{\text{initial}}$ to $\bar{A} = 0.25$)

	(I) Baseline				(II) No subjective beliefs			
		Skill				Skill		
Equilibrium	**All**	**Low**	**Medium**	**High**	**All**	**Low**	**Medium**	**High**
Partial	3	5	4	1	0	0	0	0
General	11	3	4	26	7	0	0	20

Notes: Table A31 reports the share of 18-year-olds that are strictly better off, overall and for each skill endowment, after a federal loan limit contraction from $\bar{A}_{\text{initial}}$ to $\bar{A} = 0.25$ in our model with subjective beliefs ("Baseline" columns) and in an alternative re-calibrated framework without subjective beliefs ("No subjective beliefs" columns). Rows determine the equilibrium concept being applied: "Partial" refers to a partial equilibrium exercise in which the income tax rate, prices, bequests, Social Security transfers, and the 18-year-old distribution are fixed at their initial steady state values; "General" refers to general equilibrium. For the welfare comparison in general equilibrium, the final steady state distribution of 18-year-olds was used. The share of the population that is strictly worse off is the reciprocal of those that suffer losses (that is, no 18-year-old is indifferent).

Specifically, for this limit contraction experiment, we reduce the limit by approximately one third from $\bar{A} = 0.37$ to $\bar{A} = 0.25$. Table A31 shows that some low- and medium-skill 18-year-olds are better off in partial equilibrium in the baseline, but not in the model with correct beliefs. Furthermore, general equilibrium effects dampen the extent of gains for the low-skill. Table A32 establishes the equivalence between being better off from a limit contraction in partial equilibrium and transitioning from over-enrollment in the status quo to non-enrollment in the new economy with a lower limit.

Table A32: Equivalence of better off and outflow from over- to non-enrollment ($\bar{A}_{\text{initial}}$ to $\bar{A} = 0.25$)

Initial ($\bar{A} = 0.37$) **to** $\bar{A} = 0.25$	**Outflow from over-enrollment to non-enrollment | Better off**	**Better off | Outflow from over-enrollment to non-enrollment**
	100	96

Notes: Table A32 reports statistics to establish equivalence between those strictly better off and those would flow from over-enrollment to non-enrollment when there is a contraction in the limit. Specifically, the table reports the share of 18-year-olds who would flow from over-enrollment to non-enrollment among the 18-year-olds who are strictly better off and the share of 18-year-olds who are strictly better off among 18-year-olds who would flow from over-enrollment to non-enrollment. The analyses presented in this table are from a partial equilibrium exercise in which the income tax rate, prices, bequests, Social Security transfers, and the 18-year-old distribution are fixed at their initial steady state values.