Supplemental Appendix for:
"Optimism About Graduation and College Financial Aid"

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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, US Department of Labor n.d.). 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 (Bureau of Labor Statistics n.d.).

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 I 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, or tabulations that require that we observe the respondent at age 25 (or 26 when the survey is collected every 2 years). 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 or below -2. 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 A.1 reports probit regression coefficients whose Average Marginal Effects are reported in Table 2 of Section I, as well as the pseudo-R^2.

Table A.1: 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: The table shows point estimates for probit regression coefficients whose Average Marginal Effects are reported in Table 2 of Section I. 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 A.2 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 A.2: 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 the table 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 A.3 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 separately 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 distribution is largely symmetric around 0. These results support our modeling assumption that parents have the same subjective beliefs as their child.

College enrollment rates Table A.4 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,

Table A.3: 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: The table 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.

as the calibration target.

Table A.4: 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: The table 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; for enrollment by age 25, the sample additionally conditions on observing the respondent at age 25. Source: NLSY97.

Table A.5 shows enrollment rates by age 25 broken down by parental 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 and that we observe the respondent at age 25 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.

Educational attainment outcomes versus expectations: breakdowns In Table A.6 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

Table A.5: 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: The table 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 observed at age 25 and for whom parental income is also recorded. Source: NLSY97.

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 A.6: 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: The table 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 A.7 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 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 A.7: BA enrollees who expect to earn a BA with certainty

Variable	Mean
Enrolled BA by 30	100.00 (0.00)
Expected Pr. BA by 30 (student)	100.00 (0.00)
BA by 30	69.11 (1.86)
Skill (ASVAB)	62.29 (1.01)
Female	0.64 (0.02)
Age beliefs response	15.89 (0.03)
Age in 1997	15.05 (0.06)
Real parental 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: The table 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 A.8 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 A.8: 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: The table reports the initial joint distribution of skill and parental education. Sample: high school graduates for whom we also observe parental education. 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:

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

The stochastic component is a log lag-1 autoregressive, or AR(1), process where the persistence parameter ρ_e depends on the consumer's educational attainment, as does the variance σ_e^2 of the Normal distribution from which the error term is drawn:

$$\log\left(\eta^{'}\right) = \rho_e \log\left(\eta\right) + \nu_e, \quad \nu_e \sim \mathbb{N}\left(0, \sigma_e^2\right)$$

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 $\beta_{e,1}^{A}$, $\beta_{e,2}^{A}$, and $\beta_{e,3}^{A}$ 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, $\beta_{e,s}^{s}$. Finally, using the residuals from the NLSY97 regression, we jointly estimate ρ_e and σ_e^2 for each education group. Point estimates are reported in Table A.9.

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, 2022). 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 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

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

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

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

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 A.9 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 A.10 reports the median real wage within each skill tercile by education group using the NLSY97 estimation sample for skill loadings (which is

Table A.9: Earnings process estimation results

Category	Parameter	Estimation data	Value given education e: $e=\ell$	Value given education e: $e=h$
Panel A: Age third-order polynomial	$\beta^A_{e,1}$	PSID	0.0959	0.189
	$\beta^A_{e,2}$		-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

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 A.21 of Appendix C.

Table A.10: 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: The table reports 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, $\mathbb{I}_{SC}$, with the age polynomial. Results for the interaction terms of this estimation are presented in Table A.11; these coefficients are statistically insignificant.

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 live with them and do not pay rent, we flag those residing 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

Table A.11: Robustness on pooling assumption for log wages as a function of age

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

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

are not living with their parents. 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 A.12. The average real values of the components of transfers are also reported.

Table A.12: 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: The table 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, US Department of Education, 2020). We use the public version of the HSLS:09, where information is reported up to and including the 2015-2016 academic year.

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 2017-2018. 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 their third academic year (Duprey et al., 2020)

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. 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 BA 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 A.13 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 A.13: 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: The table 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 A.14 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 quantitative 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 answered 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 A.14 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 A.14: 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: The table 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 answered 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 A.15 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 A.15: Predicting enrollment persistence (probit estimator)

	Coefficients	**AMEs**
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: The table reports coefficients and Average Marginal Effects (AMEs) 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 A.16 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 A.16 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 A.16 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 A.16, 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 A.16: 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: The table 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 (US 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 A.17 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 A.17 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 A.17: 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	1.79	0.25	0.08
	96	99	26.8				26.8	0.36	-0.44	-0.58
	91	95	23.6				23.6	0.22	-0.66	-0.78
	81	90	21.2				21.2	0.16	-0.80	-0.90
	61	80	17.9				17.9	0.11	-0.96	-1.04
	41	60	13.9	0.5			13.4	0.07	-1.14	-1.21
	21	40	9.4	2.0	1.2	0.9	5.3	0.05	-1.35	-1.37
	1	20	1.7	10.1	8.4	6.4	-23.2	0.02	-1.68	-1.59
2017	99	100	31.6				31.6	1.96	0.29	0.13
	96	99	26.5				26.5	0.38	-0.42	-0.55
	91	95	23.4				23.4	0.23	-0.64	-0.76
	81	90	21.3				21.3	0.17	-0.78	-0.88
	61	80	17.9				17.9	0.11	-0.95	-1.03
	41	60	14.0	0.5			13.5	0.08	-1.12	-1.19
	21	40	9.2	2.0	1.1	0.9	5.2	0.05	-1.34	-1.36
	1	20	1.3	9.7	8.1	5.9	-22.4	0.02	-1.68	-1.59
2018	99	100	30.2				30.2	2.00	0.30	0.14
	96	99	24.2				24.2	0.40	-0.40	-0.52
	91	95	21.9				21.9	0.24	-0.62	-0.73
	81	90	20.0				20.0	0.17	-0.77	-0.87
	61	80	16.7				16.7	0.12	-0.92	-1.00
	41	60	12.8				12.8	0.08	-1.10	-1.16
	21	40	8.1	1.6	0.9	0.8	4.8	0.05	-1.30	-1.32
	1	20	0.05	9.2	6.9	5.9	-21.95	0.02	-1.70	-1.61

Notes: The table reports the components for the estimation of the income tax progressivity parameter τ_p. 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 A.17 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 A.18; coefficients are significant at the 0.1 percent significance level. The average estimated value for τ_p is 0.177.

Table A.18: Income tax progressivity estimation results by year and overall

Coefficient	**2016**	**2017**	**2018**
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: The table 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, 2024a,b,c) to populate the 2016, 2017, and 2018 entries of Panels A, B, and C in Table A.19.

Table A.19: 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 (2024a)
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 (2024c)
G	Government	2,653,374	2,715,714	2,859,732	OECD (2024b)
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 (2024b)

Notes: The table 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 A.19. The year's estimated consumption tax is reported in its respective column of Table A.20. The parameter value for τ_c is the average across years for the 2016-2018 period: 0.043.

Table A.20: 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		

Notes: The table reports consumption tax rate estimation results, by year and averaged across years.

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 III.1, 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. 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 (4) and (5), 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 (2)-(7) 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[26]

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

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.

In the stationary equilibrium, the distribution of consumers will be stationary and all the aggregates, prices, taxes, and transfers will be constant. Additionally, all the value functions and policy functions will be time-invariant.

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))

[26]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.

3. Guess subjective value function before college, $\hat{W}_{\text{guess}}(s, \eta, a, \hat{p})$ (equation (2))

4. Use backward induction to solve consumer problem: $j = 1, \ldots, j_f + j_a$ (equations (2)-(7) and (15))-(18))

- 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., $\tilde{V}(\overrightarrow{\omega}) = V(\overrightarrow{\omega})$). 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 (6). 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 (7) 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 of expected lifetime utility 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 (2). This value function is the second of the two instances in which the planner's computation of expected lifetime utility 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 A.21 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 A.10 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.[27]

Subjective beliefs by enrollment status and skill Table A.22 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-

[27] 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 A.21: 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: The table 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 A.22: 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: The table 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 A.23 reports loan uptake by persistence status for a given cohort of enrollees in the data (Panel A, from Table 5 in Section I.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 A.23 indicates that student loan statistics by persistence status barely change when beliefs are corrected. These statistics reflect the fact that, in the model, 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 A.23, 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 A.23, 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 A.24 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 A.23: 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	12,952	12,336
C: Baseline, corrected beliefs	Did not persist	19	3	19	6,342	6,168
	Persisted	81	97	76	12,959	12,336

Notes: The table 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 A.24: Changes in student loan uptake among dropouts with corrected beliefs

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

Notes: The table 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 moving from 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-enrolled 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 A.25 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 there is a federal loan limit expansion 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 A.25: 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	-78.33	0.27	15.73
Realized	-88.74	-94.99	-88.52	-84.54	0.22	10.45

Notes: The table 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 there is a federal loan limit expansion 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 distribution of 18-year-old 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 V.2 and V.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 A.26: 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	0.68	2.17	0.97	1.01	1.07
		80 to 100	0.42	1.39	2.36	0.90	0.90	0.39
	3	*0 to 39*	0.09	0.11	0.16	0.94	0.71	0.25
		40 to 79	0.15	0.28	0.47	0.82	0.50	-0.33
		80 to 100	0.17	0.26	0.42	0.81	0.42	-0.38
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	0.59
		80 to 100	0.37	0.87	1.42	0.88	0.55	-0.26
	3	*0 to 39*	0.12	0.14	0.31	0.98	0.86	0.24
		40 to 79	0.14	0.23	0.34	0.85	0.49	-0.40
		80 to 100	0.14	0.20	0.31	0.83	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	0.86	1.19	1.00	0.00
		80 to 100	0.31	0.43	0.68	0.97	0.49	-0.36
	3	*0 to 39*	0.15	0.27	1.13	1.06	0.93	0.79
		40 to 79	0.13	0.16	0.20	0.90	0.54	-0.33
		80 to 100	0.12	0.14	0.19	0.88	0.50	-0.35

Notes: The table 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 distribution of 18-year-old 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 normalized federal loan limit to $\bar{A} = 0.56$ on the baseline model's steady state equilibrium are shown in Table A.27. 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 A.27: 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)	-5.61
Units: percentage point/percentage change	High-education labor (efficiency units)	10.85
	Labor	1.43
	Capital	0.62
	Output	1.13
	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	-10.50
	Accidental bequests	1.58
	$\mathrm{ss}_{\ell,s}$ by s	(1.32,1.37,1.49)
	$\mathrm{ss}_{h,s}$ by s	(-0.48,-0.67,-0.71)

Notes: The table 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 V.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 A.28, 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 A.28: 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
$r_t = r_{initial}$	8	4	0	21
$\gamma_t = \gamma_{initial}$	9	4	1	22
$Tr_{j,t} = Tr_{j,initial}$	8	4	0	20
$ss_{e,s,t} = ss_{e,s,initial}$	8	4	0	20

Notes: The table 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 distribution of 18-year-old 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 A.1 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 A.26); 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.

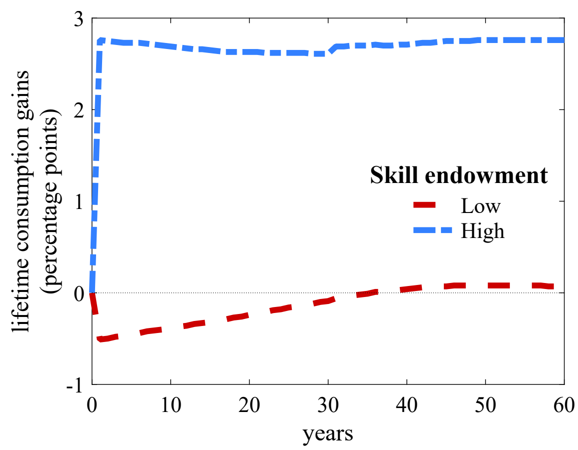

Figure A.1: Consumption-equivalent variation ($\bar{A}_{\text{initial}}$ to $\bar{A} = 0.56$)

Notes: The figure 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 V, 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 A.29, and the magnitude of the losses for those worse off by skill are reported in Table A.30.

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 A.29 shows that a slightly higher share of low-skill 18-year-olds are worse off in partial equilibrium; Table A.30 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 A.29 shows that a slightly higher share of low-skill 18-year-olds are worse off in partial equilibrium; Table A.30 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 A.29 and A.30 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 A.13 as target moments. Tables A.29 and A.30 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 A.13 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 A.29 and A.30 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 A.29: 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	21	7	0	0	21
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	8	0	0	22
Lower substitutability in low- & high-education labor:	Partial	5	12	4	0	0	0	0	0
	General	8	1	0	23	7	0	0	22
Higher (perfect) substitutability in low- & high-education labor:	Partial	4	10	3	0	0	0	0	0
	General	3	9	0	0	0	0	0	0

Notes: The table 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 distribution of 18-year-old 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 A.30: 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	$-2.96^{\dagger}$	-0.22
No learning	-0.93	-0.58	$-0.02^{\dagger}$	-0.35	-0.14	-0.25
No endogenous dropout	-0.73	-0.29	n/a	-0.23	$-2.47^{\dagger}$	-0.15
Higher add-on	-0.74	-0.24	n/a	-0.21	-0.12	-0.28
Tuition and grant | Skill	-0.47	-0.72	$-0.57^{\dagger}$	-0.21	-0.41	-0.51
Skill | Parental education	-1.03	-0.45	n/a	-0.07	-0.15	-0.13
Lower substitutability between low- and high-education labor	-0.73	-0.20	n/a	-0.10	$-3.81^{\dagger}$	-0.40
Higher (perfect) substitutability between low- and high-education labor	-1.04	-0.12	n/a	-0.58	$-4.31^{\dagger}$	$-12.00^{\dagger}$

Notes: The table reports consumption-equivalent variation estimates in units of percentage points in the model with subjective beliefs when there is a federal loan limit expansion 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 distribution of 18-year-old 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; "$\dagger$" 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 this section, we show how access to student loans can hurt some young adults by analyzing a student loan limit contraction, whereas in the experiment of the main text we analyzed a student loan limit expansion. We find that when the limit is contracted, some 18-year-olds benefit, a result consistent with that of the loan limit expansion analyzed in the main text.

We also note here that the limit contraction exercise is less susceptible to a potential concern with our main experiment regarding the fact that we impute the likelihood of continuing in college for non-enrollees. Specifically, the key mechanism highlighted in the main text's 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. In turn, the extent of optimism about the likelihood of graduation depends on both subjective beliefs about continuing 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 estimated 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 study an 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. In particular, for this population we observe graduation outcomes.

Table A.31: 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	25	8	0	0	23

Notes: The table 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, moving from $\bar{A} = 0.37$ to $\bar{A} = 0.25$. Table A.31 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 A.32 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 A.32: 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	100

Notes: The table 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.