Over-optimism About Graduation and College Financial Aid*

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Abstract

In the United States, about one in three students enrolled in a bachelor's degree program eventually drops out. The stock of student loans held by these dropouts is sizable. We establish empirically that college students and their parents are overly optimistic about the probability of college graduation when making college enrollment decisions. We incorporate such over-optimism into an overlapping generations model, which also includes family transfers, federal student loans, and a private student loan market. We discipline these model attributes using panel data from the U.S. Bureau of Labor Statistics and the U.S. Department of Education, and then examine the impact of over-optimism and of expanding federal student loan limits in the presence of over-optimism. We find that over-optimism, despite reflecting mistaken beliefs, increases welfare for 18-year-olds as a result of equilibrium adjustments in income taxes, family transfers, and skill. Expanding federal student loan limits reduces welfare for low-skill 18-year-olds from poor families, a result driven by the presence of over-optimism.

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1 Introduction

In the United States, approximately one third of students who enroll in a bachelor's program fail to complete their degree; furthermore, these dropouts hold a significant amount of student debt.[1] Previous structural studies examining college financial aid policy in the presence of dropout risk have assumed that consumers' beliefs about dropout risk are accurate.[2] We provide new empirical evidence showing that both students and their parents are overly optimistic about the likelihood of completing a college degree. We then build a general equilibrium model in which consumers solve a life cycle problem featuring college as a risky investment that can be financed with federal and private student loans, endogenous family transfers, grants, and labor earnings. Unlike previous studies, in our model consumers exhibit overly optimistic beliefs about the likelihood of college graduation, both when they choose whether to enroll in college and when they choose how much wealth to transfer to their child later in life. Such over-optimism leads to a higher college enrollment rate, and a higher level of family transfers, than would occur with accurate beliefs. We use this framework to study the impact of over-optimism on the aggregate economy and the effects of expanding federal student loan limits in the presence of over-optimism. We find that, despite reflecting mistaken beliefs, over-optimism increases welfare for young adults because it lowers the average income tax rate, raises family transfers, and raises average skill. Expanding federal student loan limits affects the welfare of 18-year-olds from low-income families the most. In this group, those with low skill see welfare losses, whereas those with high skill see welfare gains. Without overly optimistic beliefs, consumers of all skill levels would benefit from such a policy change.

Our main empirical findings are drawn from two nationally representative panel surveys: the 1997 National Longitudinal Survey of Youth (NLSY97) and the High School Longitudinal Study of 2009 (HSLS:09). In the NLSY97, we observe expectations about the high school students' probability of earning a 4-year bachelor's degree (BA) by age 30, solicited from both the student and their parent. For those who later enroll in a BA program, we construct the realized graduation rate by age 30. We show that over-optimism about college graduation, computed as the difference between the expected and realized probabilities of BA completion, is widespread. On average, college enrollees believe they have a 92 percent chance of earning a BA by age 30, yet only 70 percent of this group actually go on to earn their degree. This over-optimism is especially pronounced among those with low skill (where skill is measured with high school grade point average, or GPA), a pattern that continues to hold even when we account for gender and parental education. Moreover, parents of college enrollees exhibit similar patterns of over-optimism. In the HSLS:09,

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

[2] Notable exceptions are Matsuda (2020, 2022). We compare those two studies with ours later in this introduction.

our second main source of data, we observe uptake of federal financial aid and private student loans. By using the HSLS:09 to track a cohort of college enrollees until three years after college enrollment (before repayment begins), we show that the amount of student debt owed by college dropouts (federal or private) is economically significant at the individual level and in the aggregate.

Our model is calibrated to match moments related to overly optimistic beliefs, college enrollment and graduation, student loan uptake and repayment, and family transfers.[3] With the fully parameterized model, we perform two experiments. First, we study the impact of over-optimism by examining the effects of eliminating it from the baseline economy. We do this by setting the expected probability of continuing to the next academic year equal to the true probability. Second, in the baseline model economy with over-optimism, we expand the federal student loan limit so that federal loans can be used to pay for all four years of college. This change represents a significant expansion: under current U.S. policy and in the model's baseline economy, on average annual federal student loan limits are enough to finance only 37.5 percent of annual college costs (i.e., the average value of tuition and fees, net of grants, plus room and board). Furthermore, we provide new empirical evidence motivating the loan expansion experiment by establishing that a significant share of recent college students fully utilize their federal student loan limits under current U.S. policy.[4] In both experiments, we measure welfare using lifetime utilities computed with the correct college continuation probabilities, but taking as given consumer choices which are made based on their beliefs.

In the first experiment, we find that eliminating over-optimism reduces welfare for the average 18-year-old in general equilibrium, despite correcting mistaken beliefs. While there are small gains for some skill levels in the initial periods of the transition, by the later periods of the transition losses reach 0.9 percent of lifetime consumption. Eliminating over-optimism uncovers its complex role in the economy: although the presence of over-optimism leads 18-year-olds to enroll in college when they otherwise would not (thereby generating "over-enrollment"), over-optimism also benefits these young adults in general equilibrium. Most importantly, these benefits arise precisely because over-optimism raises the college education rate by boosting enrollment rates above what they would be with correct beliefs. A higher college education rate expands the income tax base and raises output. When this happens (even with government consumption specified as a constant

[3] We are able to document that college students are overly optimistic on either side of the college enrollment decision, but the data are not sufficient to establish learning dynamics while enrolled in college. To be conservative about the consequences of over-optimism, in our model college students learn the truth about the likelihood of college graduation at the start of their first academic year, before making any decisions. College students are then are allowed to choose to drop out before beginning their second academic year.

[4] Sources for borrowing limits: Smole (2019) and NCES (2019), authors' calculations. Sources for utilization rates: HSLS:09 and Smole (2019), authors' calculations. For a broader discussion of borrowing constraints and post-secondary education, see Lochner and Monge-Naranjo (2016).

fraction of output), our model's progressive income tax system allows the government to balance its budget with a lower average income tax rate, which benefits all 18-year-olds. This mechanism highlights that the positive fiscal externality of a college degree is partially offset by overly optimistic beliefs. Furthermore, over-optimism raises the inter vivos transfer that 18-year-olds receive from their parents and raises the average skill endowment because child skill is positively correlated with parental education.

Our second experiment highlights the implications of over-optimism for the effects of college financial aid policy. In particular, we find that expanding federal student loans limits leads to heterogeneous welfare changes among 18-year-olds from poor families. In that group, those with low skill see losses ranging from 1.3 to 2.6 percent of lifetime consumption, whereas those with high skill see gains ranging from 1.4 to 4.3 percent of lifetime consumption. Welfare losses for those with low skill arise because access to more federal loans greatly increases their ability to finance college and thus worsens the extent of their over-enrollment. We are able to uncover this heterogeneity in welfare effects because we incorporate over-optimism into the model environment: in supporting analysis, we show that in a model economy without over-optimism such an expansion in federal student loan limits benefits 18-year-old consumers at all levels of skill.

This study is not the first to examine college enrollment and college financial aid policies. Indeed, previous related work—which includes Caucutt and Kumar (2003), Ionescu (2009), Lochner and Monge-Naranjo (2011), Chatterjee and Ionescu (2012), Krueger and Ludwig (2016), Ionescu and Simpson (2016), Luo and Mongey (2019), Abbott, Gallipoli, Meghir, and Violante (2019), and Caucutt and Lochner (2020)—also examines the role of federal and private loans, public grants, and family transfers. A key assumption maintained in these studies is that student and parent expectations about academic outcomes are consistent with realized outcomes; in those studies, a direct impact of higher financial aid is higher welfare. We build on that literature and, motivated by our empirical findings, incorporate over-optimism about the likelihood of college graduation. We demonstrate that, with over-optimism, more financial aid reduces welfare for some consumers.

Two structural studies that also consider over-optimism in the context of post-secondary education are Matsuda (2020) and Matsuda (2022). Both of these papers incorporate over-optimism about college "ability", which gives rise to over-optimism not only about graduation likelihood, but also the college wage premium and the ability of one's future children. Matsuda (2020) examines the design of public grants, while Matsuda (2022) compares public grants with progressive income taxation as sources of social insurance. In both Matsuda (2020, 2022), the comparison is solely across steady states. In contrast, we use new empirical evidence to motivate the specific over-optimism about graduation likelihood that we include in our model environment; additionally, our experiments focus both on uncovering the role of over-optimism and on examining its implications for federal student loan limit expansions. Our study analyzes changes along transition paths as well as across steady states.

Our empirical evidence on over-optimism about the likelihood of college graduation complements previous work by Stinebrickner and Stinebrickner (2012). That study examines a small panel survey of students at a single U.S college in the early 2000s, and finds that students are overly optimistic about their academic performance in college. Using this information, the authors then infer the extent of over-optimism about the likelihood of college graduation and find it to be sizable. We use reported expectations about education attainment in the NLSY97, a nationally representative public survey, to provide new evidence that high schoolers are overly optimistic about their likelihood of attaining a bachelor's degree. Furthermore, we document similar over-optimism among parents about their child's prospects.

Our empirical work also provides discipline for the private student loan market in our model environment. The role of private student loans as a source of college financing has been emphasized in previous work: as argued by Lochner and Monge-Naranjo (2011), including private student loans in studies of college financial aid policy is important because the private market provides an outside option to the government financial aid program. However, while the current literature has routinely incorporated key features of the federal student aid program into their model frameworks, there is less consensus about modeling the private student loan market. For example, Lochner and Monge-Naranjo (2011) assume that lenders set loan interest rates using repayment risk that depends on student skill, making low-skill students less likely to have access to private student loans relative to their high-skill peers. Ionescu and Simpson (2016) assume that private lenders price the student loan based on the inherent credit risk of the borrower. Abbott, Gallipoli, Meghir, and Violante (2019) assume that students from low-income families do not have access to private student loans. We contribute to the aforementioned literature by using the HSLS:09 and the 2019 Survey of Consumer Finances (SCF) to document key attributes of the U.S. private student loan market, which are then reflected in our model framework.

Our findings documenting student debt among dropouts complements the work of Chatterjee and Ionescu (2012), which uses the SCF to show that outstanding balances held by college dropouts are significant. While our main empirical takeaways are similar, we expand this analysis in two ways. First, we use the HSLS:09 to document significant balances among dropouts by tracking a single cohort of college students until three academic years after enrollment. This approach allows us to avoid measuring balances in a cross-sectional sample like that of the SCF, with the potentially large heterogeneity in federal policy regimes at loan issuance, time in repayment, labor market experience, and other factors that such a sample implies. Second, our HSLS:09 findings on student debt balances are drawn from student records submitted by post-secondary institutions, which are likely to be a more reliable source of information than self-reported balances recorded in the SCF.

Our study also contributes to the consumer credit literature on over-borrowing. Related work includes Nakajima (2012, 2017); these papers examine the impact of increased access to unsecured credit (e.g., credit cards) and bankruptcy policy reforms when consumers have time inconsistent preferences. Another example is Exler, Livshits, MacGee, and Tertilt (2021), which analyzes policies aimed at correcting for over-borrowing in the unsecured credit market resulting from over-optimism about earnings. One of the key takeaways from these studies is that quantity restrictions, even in the presence of over-borrowing, lead to welfare losses. We contribute to this literature in two ways. First, we focus on student loans rather than unsecured credit and find that expanding federal borrowing limits (reducing quantity restrictions) leads to welfare losses for low-skill 18-year-olds from poor families. Second, we address a challenge for the consumer credit literature by incorporating empirical discipline for the bias present in our model: in particular, we leverage data on expectations about the likelihood of earning a bachelor's degree and realized educational outcomes to pin down the extent of over-optimism.

This paper proceeds as follows. Section 2 overviews our empirical findings. Section 3 lays out the model, Section 4 describes the model parameterization, and Section 5 analyzes properties of the model's initial steady state equilibrium. Section 6 reports the results of our main experiments. Section 7 concludes.

2 Data

The two main datasets we draw on are the 1997 National Longitudinal Survey of Youth and the High School Longitudinal Study of 2009. These are supplemented with the 2019 Survey of Consumer Finances. All of these surveys are collected within the United States.

The NLSY97 is a nationally representative panel survey that follows young adults born between 1980 and 1984 ("sample members") from 1997 until 2019. It is collected by the U.S. Bureau of Labor Statistics (Bureau of Labor Statistics, U.S. Department of Labor, 2019). The NLSY97 provides information on expected probabilities of earning a bachelor's degree for sample members and their parents, as well as realized education outcomes, which we use to document over-optimism about the likelihood of college graduation.[5]

The HSLS:09 is a nationally representative panel survey that follows a sample of ninth-grade students from 2009 until 2016, although some information from post-secondary transcripts and student records is collected after 2016. It is conducted by the National Center for Education Statis-

[5]We use "college" to refer to a 4-year bachelor's degree program throughout this paper.

tics (NCES), a subsidiary of the U.S. Department of Education (U.S. Department of Education, 2020a). Unlike the NLSY97, the HSLS:09 follows a cohort that interacted with the most recent iteration of U.S. financial aid policy, to which we calibrate our structural model (e.g. borrowing limits set in 2012). We use the HSLS:09 to document student loan uptake and balances by college persistence status. We also document the composition of student debt portfolios by loan type (i.e., federal or private) and private loan uptake patterns by high school GPA and family income.

The 2019 SCF is a nationally representative cross-sectional survey of families that is conducted every three years. It is sponsored by the Federal Reserve Board of Governors and the U.S. Department of the Treasury (Board of Governors of the Federal Reserve System, 2019). The SCF reports interest rates for federal and private student loans for which respondents still owe a positive amount when the survey is conducted. Together with findings on private student loans from the HSLS:09, we use interest rates by loan type from the SCF to discipline model attributes of the private student loan market.

2.1 Over-optimism about the likelihood of college graduation

The NLSY97 asks sample members twice about their expected probability of earning a BA by age 30: once in 1997 and again in 2001. The survey also asks parents the same question about their child, but only once, in 1997. This question can be paraphrased as: "What is the percent chance that [you/your child] will have a four-year college degree by the time [you/they] turn 30?" The response is a percentage value between 0 and 100. The NLSY97 also reports the high school GPA, college enrollment, and educational attainment of sample members over the course of the panel. We assign each sample member to a skill quantile using the distribution of high school GPA among high school graduates.[6] We also flag those who had enrolled in a BA program, as well as those who had earned a BA, by age 30.[7]

Using this information, Panel A of Table 1 compares averages of sample member expectations about the likelihood of college graduation with realized graduation rates, by skill quantile. The first column reports the skill quantile, which is assigned using the distribution of high school graduates (note that Panel A's sample is then restricted to those who enrolled in a BA program sometime before turning 30).[8] The second column contains the number of observations in each

[6] We use high school GPA to measure skill because it is in both the NLSY97 and the HSLS:09, and we want to measure within-skill quantile values of various variables in both data sources. Unlike the NSLY97, the HSLS:09 does not contain a variable recording a score for the Armed Services Vocational Aptitude Battery.

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

[8] The tabulation is done for the sample of high school graduates who eventually enroll in a BA program to focus on over-optimism about college *graduation*, rather than about college enrollment. Because of the way the survey question is structured, an expected probability response that is solicited in high school combines the expected probability of enrolling in college with the expected probability of completing college conditional on enrollment. For those who

skill quantile for the sample of college enrollees. The mean expected probability of earning a BA by age 30 is reported in the third column; to construct expectations about the likelihood of college graduation collected before, but as close as possible to, the college enrollment decision, we use the most recent valid response to this question collected while the respondent was enrolled in high school. The fourth column contains the realized graduation rates computed as the frequency of BA attainment by age 30. The last column reports the percentage point difference between average expected probabilities and the realized probability, which represents the extent of over-optimism for the skill quantile. Panel A indicates that, within each skill quantile, the expected probability of earning a BA by age 30 is much higher than the realized rate of attaining that outcome. This is especially true for those with the lowest skill, whose over-optimism is about 50 percentage points, compared to those with the highest skill, whose over-optimism is about 15 percentage points.

Panel A documents overly optimistic beliefs collected while the respondents are in high school, conditional on their eventually enrolling in a BA program. Does the over-optimism documented in Panel A persist until the college enrollment decision? We argue that it does and offer supporting evidence by examining a group of respondents for whom we can measure overoptimism on both sides of the college enrollment decision. Specifically, we restrict attention to sample members who answer the 1997 question while still in high school and also answer the 2001 question while enrolled in a BA program. The results are shown in Panel B of Table 1.[9] If these individuals were changing their expectations right before college enrollment to be closer to the realized probability of graduation, then one could safely presume that the expected probability after enrolling would be closer to the realized probability of graduating, which is about 70 percent. In fact, the expected graduation likelihood increases slightly from 92 to 93 percent.

Panel C reports the same statistics as Panel A but for parental expectations about their child's prospects. Because this panel conditions on observing the parents' expected probabilities of their child earning a BA, the sample differs slightly from that of Panel A. Consequently, the college completion rates by skill quantile change slightly. Panel C indicates that parents, like their children, are overly optimistic about their child's prospects for earning a BA, and to a similar extent as their child.[10]

eventually enroll in college, it is not a heroic assumption to impose that expected probability of enrollment was 1 and interpret the response as the conditional probability of completion. Of course, for the same reported expected probability, lowering the expected probability of enrolling that we assume would raise the implied conditional probability of graduating once enrolled. In that sense our assumption makes the over-optimism findings in Table 1 lower bounds.

[9]We do not break down these statistics by skill quantile because the sample size is small, which occurs for two reasons. First, a small proportion of respondents meet the education timing criteria. Second, in the 2001 NLSY97 questionnaire, respondents were divided into four groups for the beliefs questions, and only groups 1 and 3 were asked about educational attainment expectations.

[10]Parents and children also report very similar likelihoods of college attainment within families: the median difference in expected probabilities of the parent and their child is zero. See Table 15 and the associated discussion in

Table 1: Over-optimism about the likelihood of graduating from a Bachelor's program by age 30

			(a) **Mean expected graduation prob.**	(b) **Realized graduation rate**	**Over-optimism** $(a)-(b)$
Panel A	**Skill**	**Obs**			
Student over-optimism by student skill quantile among college enrollees	1	222	81.78	31.98	49.80
	2	395	87.42	55.95	31.47
	3	587	93.56	78.19	15.36
	Obs	1,204			
Panel B	**Response timing**		(a) **Mean expected graduation prob.**	(b) **Realized graduation rate**	**Over-optimism** $(a)-(b)$
Student over-optimism by response timing among college enrollees	Before enrollment		92.07	69.62	22.45
	After enrollment		93.14	69.62	23.52
	Obs	316			
Panel C	**Skill**	**Obs**	(a) **Mean expected graduation prob.**	(b) **Realized graduation rate**	**Over-optimism** $(a)-(b)$
Parent over-optimism by student skill quantile among parents of college enrollees	1	166	80.93	31.33	49.61
	2	297	84.79	54.88	29.91
	3	429	93.03	78.79	14.24
	Obs	892			

Notes: Panel A of Table 1 compares students' mean expected probability of earning a BA program by age 30 with the realized graduation rate within each student skill quantile for the sample of respondents who enrolled in a BA program by age 30; Panel B compares the expected probability of earning a BA collected before and after college enrollment with the realized graduation rate for the sample of respondents who were enrolled in high school in 1997, were enrolled in a BA program in 2001, and who also answered the education expectations question in both years; Panel C compares mean parental expectations for their child's likelihood of earning a BA with realized graduation rates by student skill quantile for the sample of students who enroll in a BA before age 30 whose parents were asked the expected education question while their child was in high school. Skill quantiles are assigned using the distribution of high school GPA among high school graduates. Expectations, graduation rates, and over-optimism are all in units of percentages. Source: NLSY97.

Do educational attainment beliefs reported in the NLSY97 predict actions? We apply this question to the college enrollment decision in particular, and in Table 2 we report results for a regression in which the dependent variable is a flag for enrolling in a BA program before age 30 (which takes a value of 100 if the individual enrolled, 0 otherwise), and the independent variables include the respondent's expected probability of earning a BA degree before age 30 (a value between 0 and 100). Additional controls are also included: model (1) controls for the respondent's skill (measured with high school GPA) and gender, while model (2) adds family characteristics (i.e., family income and parent education). The estimator is Ordinary Least Squares. Our results indicate that enrollment in a bachelor's degree program is positively predicted by the sample member's expected probability of earning a BA, even when controlling for the respondent's individual and family characteristics. Specifically, in model (1) a 1 percentage point increase in the expected probability of earning a BA implies a 0.515 percentage point increase in the probability of enrolling

Supplementary Appendix A.1.

in a BA program. This effect falls slightly to 0.473 when we control for family characteristics in model (2). In both model (1) and model (2), the marginal effect of respondent beliefs is highly statistically significant.[11]

Table 2: BA enrollment by age 30 as a function of the expected probability of earning a BA

	Enrolled in a BA program by age 30	
Controls	**(1)**	**(2)**
Expected probability of earning a BA by age 30	0.516 (0.0329)	0.473 (0.0403)
High school GPA	30.38 (1.652)	26.05 (1.975)
Male	-1.086 (1.806)	0.203 (2.139)
Age in 1997	0.220 (0.648)	-0.0833 (0.747)
Logged family income		6.395 (1.099)
At least one parent BA+		13.96 (2.695)
Constant	-80.32 (11.29)	-130.1 (16.06)
R^2	0.259	0.297
Obs	2,367	1,656

Notes: Table 2 presents estimation results from two models. The dependent variable for both models (1) and (2) is a flag for enrollment in a BA program by age 30, which takes a value of 100 if the individual enrolled in a 4-year program BA program by age 30 and 0 otherwise. From top to bottom, the controls are the expected probability of earning a BA by age 30 (respondent beliefs, with a range between 0 and 100); the respondent's high school GPA (between 0 and 4); an indicator set equal to 1 if the respondent is male and equal to 0 otherwise; the respondent's age in 1997; the log of family income for the respondent while they are in high school; an indicator equal to 1 if at least one resident parent has a bachelor's degree or more and equal to 0 otherwise; and a constant. Samples: model (1) is high school graduates; model (2) is high school graduates, conditional on observing family income and parent education. Standard errors in parentheses. Source: NLSY97.

In Table 16 of Supplementary Appendix A.1, we show how over-optimism for each skill quantile varies by gender and parental education and find that low-skill college students continue to exhibit sizable and relatively higher over-optimism within each gender and parental education grouping.[12] We also show supporting evidence for our over-optimism findings in the NLSY97 from an addi-

[11] The fact that reported beliefs about college degree attainment are positively correlated with college enrollment rules out beliefs being driven entirely by a sense of "social desirability", that is, students saying what they think others want to hear.

[12] Although Table 2 shows that there is selection into college by expected probability of earning a BA, the beliefs of those who do not enroll still exhibit sizable over-optimism for those with low skill. Over-optimism is also present, but at lower magnitudes, for those with medium skill levels among non-enrollees. This is demonstrated in Table 17 and the surrounding discussion in Supplementary Appendix A.1.

tional dataset, the HSLS:09, in Table 23 of Supplementary Appendix A.3.[13] However, our main findings from the HSLS:09 relate to student loans, and in the next section we use that dataset to document how uptake of student loans varies by college persistence status.

2.2 Student loan uptake and balances

The HSLS:09 contains information about the focal ninth-grade high school student (e.g., their total high school GPA and their expected educational attainment) as well as about their family (e.g., family income and parental education). For the vast majority of sample members, high school graduation occurs in the spring of 2013. The HSLS:09 also contains information on student loan balances, if any, collected from student records submitted by post-secondary institutions. We use the HSLS:09 to demonstrate that there is sizable student loan uptake among those who enroll in a BA program but do not persist toward graduation.[14]

We restrict our sample to students who graduated from high school by the summer of 2013 and enrolled in a BA program in the fall of 2013. Among this group, we additionally restrict attention to individuals for whom we observe family (parent) income, biological parental educational attainment, and the student's high school GPA. We also require that the student reports their educational attainment expectations in the spring of their junior year of high school.[15] In Table 3, we report loan statistics by persistence status; by "persisting" we mean maintaining enrollment in their program from the first year (the 2013-2014 academic year) through their third year (the 2015-2016 academic year). Someone who does not persist leaves college for at least one academic year after enrolling. Unlike the NLSY97, the short panel dimension of the HSLS:09 prevents us from using more long-term measures of college completion, so we largely avoid using terms such as "dropout" in our discussion of the HSLS:09 findings.

Table 3 shows that 24 percent of the enrolled population fail to persist toward college completion. Those who do not persist owe 19 percent of the sample's student debt balances (either federal or private) and are more likely to have student debt relative to those who persist. Conditional on having student debt, the average and median student loan balance is economically significant

[13]The HSLS:09 also provides a source of supporting evidence for the NLSY97 over-optimism findings. See Supplementary Appendix A.3. In the HSLS:09, there is no age limit condition on the outcome being asked about, and the response is categorical (e.g., "Bachelor's") rather than a continuous probability. That is why our main results on over-optimism are established with the NLSY97. However, if one is concerned about survey respondents being confused by probabilities, then the categorical form of the HSLS:09 expectations questions may make our over-optimism results more convincing.

[14]All tabulations of HSLS:09 data, both here and in the Supplementary Appendix, use survey weights. The specific weights used for each tabulation are noted in each table's footnote.

[15]This approach allows us to use a consistent sample for both the student debt findings and a comparison of over-optimism in the HSLS:09 with findings in the NLSY97.

several years after enrollment, regardless of persistence status. This is true despite non-persisters using that money to finance fewer years of tuition, compared to students who persist toward degree completion. In the next section, we focus particularly on private loans using information from the HSLS:09 and the 2019 SCF, interpreted using several additional sources.

Table 3: Student loan incidence by persistence status

Persistence status	**% of enrollees**	**% of SL $**	**% with SL**	**Average $**	**Median $**
Did not persist	24	19	78	15,270	12,238
Persisted	76	81	65	24,648	19,500
Obs	2,356				

Notes: Table 3 divides the pool of 2013 bachelor's degree enrollees into students who persisted in college and those who did not persist. Persistence status is assigned based on whether their student record indicates that they were enrolled for each academic year between 2013-2014 and 2015-2016. Within each persistence status group, the table reports the group's percentage of 2013 enrollees, the dollars owed by the group as a percentage of aggregated student debt among 2013 enrollees, the percentage of the group with a positive student debt balance, and the average and median student loan balance owed by debtors in the group after three academic years, in 2016 dollars. Percentages are rounded to the nearest percentage point. Weights are PETS-SR student records longitudinal weights. Source: HSLS:09.

2.3 Private student loans

The private student loan market warrants further examination as it is the source of a potential substitute for federal loans, which is relevant for our loan limit expansion exercise. We begin with information from the HSLS:09 reported in Table 4, which summarizes sources of student loans three academic years after enrollment among 2013 college enrollees. Results are broken down separately for each persistence status. Moving from left to right, the columns report, first, the percentage of the group that has either federal or private student loans; second, the percentage that has only federal loans; third, the percentage with only private loans; and fourth, the percentage with debt from both kinds of student loans. This table has two main takeaways, which hold for both persistence statuses: first, more than one in five students take out a private student loan during college, indicating that using this source of financing is somewhat common; and, second, there is a pecking order for loan types, where students tend to take out a federal loan and then sometimes turn to private loans. For intuition about the second takeaway, note that if students often took out private loans without first using federal loans, then the share of student debtors with only private loans would be more similar to the share with only federal loans. However, Table 4 shows that this is not the case in the data: for both persistence groups the share with only private student loans is almost 0, whereas the share with only federal loans is quite large.

The HSLS:09 also sheds light on access to private student loans by key student characteristics.

Table 4: Student loan portfolio composition

Persistence status	Either	Only federal	Only private	Both
Did not persist	78	53	1	24
Persisted	65	44	2	20
Obs	2,356			

Notes: Table 4 reports, by persistence status, the percentage of all 2013 bachelor's degree enrollees who owe money for either, only federal, only private, or both types of student loans three years after enrollment. Percentages are rounded to the nearest percentage point, so the sum of the last three columns may not exactly equal the value in the first column. Weights are PETS-SR student records longitudinal weights. Source: HSLS:09.

Table 5 reports uptake rates for private loans, computed as the percentage of each quantile of the joint distribution of family income and skill that has taken out a private student loan three academic years after they began college. Family income and skill quantiles are assigned using the distribution of each variable among high school graduates. This table illustrates that college students from the poorest families and college students from the lowest skill take out private loans like their richer and higher-skill peers. Because access is a necessary condition for uptake, and quantiles are assigned using the distribution of high school graduates, the results in Table 5 reject the hypothesis maintained in previous studies that low-skill or low-income prospective college students are barred from the private student loan market.

To be clear, we do not claim to demonstrate that all prospective college students necessarily have access to private student loans. In order to examine what is driving the findings of Table 5, we turn to industry reports and guides for potential private loan borrowers. Based on these sources, it seems that with most private lenders having a cosigner is a sufficient condition for access to private student loans at good terms, yet the presence of a qualifying cosigner is likely not highly correlated with skill or family income. Among the five largest private student lenders, 90 percent of undergraduate student loans issued since 2010 have had a cosigner (Amir, Teslow, and Borders, 2021).[16] Most adults qualify as cosigners for private student loans: for loan approval, the minimum credit score requirements range from none to 680, and even cosigners without a credit score could still qualify with some lenders if their income is steady and meets a low threshold level (Holhoski et al., 2022).

The HSLS:09 does not report the student loan's interest rate, so we turn to the 2019 SCF to compare interest rates on private and federal student loans. For a given family, the SCF records information on up to six student loans; each loan is associated with a separate set of variables that record re-

[16]For students without a cosigner, it is much more difficult to get any private student loan in the freshman and sophomore years of college. However, in the junior and senior years of college, students with a credit score and a steady income can get a private student loan. For an example of a private student loan that does not require a cosigner, see Funding U., Inc. (2022).

Table 5: Private loan uptake rates

		GPA		
	Q	**1**	**2**	**3**
Income	**1**	19	25	16
	2	26	31	24
	3	39	21	19
Obs	2,356			

Notes: Table 5 reports the percentage of each cell that has a positive private student loan balance three academic years after enrollment in the fall of 2013. Percentages are rounded to the nearest percentage point. Rows are student family income quantiles using parents' income during high school; columns are high school GPA quantiles. Quantiles are assigned using the distribution of high school graduates. Weights are PETS-SR student records longitudinal weights. Source: HSLS:09.

sponses to various questions about that loan, such as the interest rate or the type of loan (federal or private). We separate student loans into federal or private loans and report the mean and median of interest rates within each loan type in Table 6, both overall and by the borrower outcome groupings of income, education, and delinquency status.[17] These three statistics are very similar across the two loan types (column 2). The observed low standard deviation of private loan interest rates (comparable to federal interest rates) is likely a result of most private student loans having a cosigner, where having a cosigner leads to more favorable terms regardless of other student attributes (Holhoski, Clark, and Beresford, 2022). Columns 3 to 6 of Table 6 break down interest rates by income quantile, while the remaining four columns break down interest rates by graduate status (that is, education outcome) for all families and for families who are delinquent.[18] Along all of these margins, the difference between federal and private student loans in the mean or median interest rate is small. These findings indicate that private and federal student loans do not differ significantly in their interest rates, and that the the relationship between debtor attributes and interest rates on private loans is similar to that of debtor attributes and interest rates on federal loans (which are set by statute).

[17] All tabulations of 2019 SCF data use survey weights.

[18] Graduate families (for whom the graduate status is "Yes") have completed at least one of the programs for which they took out their education loans. Delinquent families have at least one education loan for which they are late making payments.

Table 6: Student loan interest rates

		All families					Delinquent families	
		Income quantile			Graduate status		Graduate status	
Loan type	**All families**	**1**	**2**	**3**	**Yes**	**No**	**Yes**	**No**
Federal								
Mean	5.97	5.95	6.08	6.26	5.92	6.29	6.02	6.88
Median	5.50	5.50	5.32	5.96	5.50	5.60	6.00	6.00
Obs	3,841	592	1,647	1,602	2,658	675	202	194
Private								
Mean	5.85	5.65	5.95	6.78	5.86	6.07	6.18	6.90
Median	5.84	6.00	4.85	6.38	5.84	5.40	6.70	6.00
Obs	779	85	253	441	554	144	52	30

Notes: Table 6 reports interest rates for federal and private student loans for all families (column 2), by income quantile within all families (columns 3, 4, and 5), by educational attainment within all families (columns 6 and 7), and by educational attainment within delinquent families (columns 8 and 9). Graduate families (for whom the graduate status is "Yes") have completed at least one of the programs for which they took out their education loans. Delinquent families have at least one education loan for which they are late making payments. Source: 2019 SCF.

In the next section, we build a model framework that incorporates our empirical findings from Sections 2.1 and 2.3 on over-optimism, uncertainty about college persistence, financial aid, and the private student loan market. Our findings on student loan uptake in Section 2.2 are used to validate the calibrated model in Supplementary Appendix C.1.

3 Model

Our model economy builds on Krueger and Ludwig (2016), Chatterjee and Ionescu (2012), and Luo and Mongey (2019). Motivated by our findings in Section 2.1, we enrich the general equilibrium life cycle model with college choice of Krueger and Ludwig (2016) by incorporating over-optimism about likelihood of college graduation. We also incorporate endogenous and exogenous college dropout, as in Chatterjee and Ionescu (2012), as well as key features of the U.S. market for student loans. The features of the federal student loan program are largely based on Luo and Mongey (2019), and the features of the private student loan market are based on empirical patterns documented in Subsection 2.3.

3.1 Overview

Time is discrete and runs forever; each period lasts one year. Although we compute transition paths for our analyses, we omit time subscripts for the purpose of exposition. There are four main kinds of agents in the economy: consumers, the government, private lenders, and a final goods firm.

Consumers Let j denote the age of consumers; consumers start making decisions when they turn 18 at $j = 1$. With an exogenous probability q, 18-year-old consumers may choose whether to enroll in college; otherwise, college is not an option, and they join the workforce without a college degree.[19] The college entrance decision will be based on skill, s, idiosyncratic earnings productivity, η, and initial net assets, a. Skill is an endowment drawn once from a conditional distribution that depends on parental education.[20] The skill endowment determines the consumer's expectations about their continuation probability in each year of college at the time of enrollment, the true probability of continuation given enrollment, deterministic earnings productivity, and proportional grants for college from the government and private sources. The idiosyncratic productivity component of earnings follows a lag-1 auto-regressive, or AR(1), process that depends on completed education. Net assets are determined at the start of adulthood by a one-time inter vivos transfer from the consumer's parent.

When making the college entrance decision, consumers with skill s believe they will continue their education in each year of college with probability $\hat{p}(s)$. The true annual probability of continuing a college education is $p_c(j, s)$. Consumers are overly optimistic as long as $\hat{p}(s) > p_c(j, s)$ for all s and j, with higher $\hat{p}(s) - p_c(j, s)$ implying higher over-optimism. If $\hat{p}(s) = p_c(j, s)$, consumers have the correct beliefs about the probability of continuation (and therefore about the likelihood of graduation). Our first experiment will study the impact of over-optimism by setting $\hat{p}(s) = p_c(j, s)$.

The over-optimism discussed in the previous paragraph implies that consumers in our model deviate from rational expectations in the following way: 18-year-olds making the college enrollment decision (and their parents) believe that they are unique when it comes to their probability (or their child's probability) of continuing from one academic year to the next. Consumers understand everything else about their environment: they know others are overly optimistic, their own skill, and how skill affects earnings. Because individuals are atomistic, they can believe that their own continuation probability is uniquely higher than others of the same skill type, and take as given aggregate endogenous states which are computed using enrollment decision rules of overly optimistic consumers and then simulated with the true continuation probabilities.

Consumers learn their true probability of continuing in college immediately after enrollment. In

[19]This model feature captures personal or family reasons that lead consumers to not go to college. See Table 25 in Supplementary Appendix A.3 for suggestive empirical evidence. An alternative modeling approach is to assume stochastic utility costs to go to college, as in Abbott, Gallipoli, Meghir, and Violante (2019). Our approach is a nested version of stochastic utility costs, where with probability $1 - q$, the cost is large enough so that those consumers will not go to college.

[20]Supplementary Appendix C.3 presents the case where skill does not depend on parental education. The main results do not change.

principle, this assumption minimizes the impact of over-optimism on consumer behavior.[21] After the first year of college, consumers may be forced to leave college with an annual probability $1 - p_c(j, s)$ (exogenous dropout); otherwise, consumers may choose to leave college (endogenous dropout).[22]

Earning a college degree requires four completed years of enrollment. The benefits of graduating from college are higher labor earnings, a higher probability of having high-skill children, and higher Social Security transfers.[23] The costs of college are foregone earnings due to part-time work, a college effort cost net of college consumption value, and an annual pecuniary cost (tuition and fees). College expenses including room and board can be financed with student loans borrowed from the federal student loan program and the private loan market, inter vivos transfers from parents, grants from public and private sources, and earnings from part-time work.

After the age of college graduation, consumers with an outstanding student loan balance may be either college graduates or college dropouts. At this point, consumers begin to make decisions on whether to make loan payments: in particular, they may choose to repay only federal loans, only private loans, both types of loans, or neither type of loan.[24] Upon paying off student loans, consumers may save and solve a standard consumption-savings problem.[25] Consumers who do not make payments on their student loans are considered delinquent, and their disposable income above the amount $\bar{y}$ is garnished at the rate τ_g. Delinquent debtors also incur a collection fee and a stigma cost for the particular year and loan on which they are delinquent.[26]

All consumers have a child at the fertile age, j_f; this child will leave the household j_a years after birth. At the beginning of the period when the child leaves, as in Krueger and Ludwig (2016) and

[21] However, quantitatively, this assumption does not matter: in Supplementary Appendix C.3, we consider a sensitivity analysis where college students never learn about their true likelihood of continuation.

[22] Exogenous dropout represents college students who leave because of a lack of academic ability. This attribute is supported by the findings in Stinebrickner and Stinebrickner (2012), which show that heterogeneity in ability, rather than heterogeneity in effort, leads to college dropouts. For example, even for students in the same major who put in the same hours of study, the paper finds significant differences in academic performance.

[23] Consumers must graduate from college to enjoy these benefits. In Table 20 of Supplementary Appendix A.2, we show that, relative to having only a high school degree, the marginal effect of some college (college dropouts or those with an associate's degree) on the age profiles of earnings is approximately zero.

[24] In our model, it is not possible to have an outstanding student loan, federal or private, written off via default. This is consistent with the U.S. federal student loan system, as well as with private student loan policies. Student loans may eventually be classified as defaulted loans, but are almost never discharged.

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

[26] These garnishment rules reflect the U.S. system, where both federal and private lenders may garnish earnings (private lenders require a court order).

Abbott, Gallipoli, Meghir, and Violante (2019), each parent makes an inter vivos transfer to their child after observing the child's skill, s_c. This transfer is motivated by parental altruism, where the parent's beliefs about the likelihood of their child continuing toward college completion are built into the altruism term included in their objective function. The parameterized model will feature parents who are overly optimistic about their child's likelihood of continuing in college, reflecting our findings in Section 2.1. Consumers retire at age j_r. At this point, they stop working and receive Social Security transfers. Consumers survive each period with probability ψ_j, and live for a maximum of J periods.

Government The federal student loan program is characterized by a cumulative student loan limit $\bar{A}$ and a student loan interest rate $r_{SL} = r + \tau_{SL}$, where r is the risk-free interest rate on savings and τ_{SL} is the add-on set by the government. For our second experiment, an expansion in federal student loan limits, we increase $\bar{A}$ from its baseline value. Federal student loans are assessed interest starting from the year after the age of college graduation ($j > 4$), implying that there is an interest-free grace period for federal student loans for the duration of the college years (that is, all federal student loans are subsidized).[27]

In addition to running the federal student loan program, the government provides grants for college education and funding for Social Security, and also faces an exogenous government consumption requirement expressed as a fixed fraction g of gross domestic product (GDP). Expenditures are financed with revenue generated from progressive income taxes and a flat-rate consumption tax.

Private lenders The private student loan market is characterized by a continuum of risk-neutral competitive lenders. The features of the private loan market are based on findings from our empirical analysis in Section 2.3. First, to capture the pecking order from federal to private student loans shown in Table 4, we introduce a loan uptake cost specifically for acquiring private student loans. This cost makes private student loans an imperfect substitute for federal student loans; it represents the additional effort required in the private student loan market to avoid predatory lending and hidden fees, as well as potential difficulties in acquiring a cosigner or even finding a lender. Second, we do not explicitly exclude any consumer from access to the private student loan market, which is consistent with positive private loan uptake patterns observed in Table 5. Third, we incorporate a student loan issuance cost that is common to both private and federal student loans, τ_{is}, to cap-

[27]The federal student loan program modeled here abstracts from unsubsidized loans and other features such as loan fees and the Expected Family Contribution (EFC). In Supplementary Appendix C.3, we show that our main findings do not change if we incorporate a higher add-on for the student loan interest rate as a sensitivity analysis for the lack of unsubsidized loans and loan fees. We do not view the lack of an explicit model counterpart to the EFC as a concern for our findings because the borrowing limits we currently use represent upper bounds on yearly loan amounts, and introducing heterogeneity in borrowing limits resulting from EFCs would simply constrain some agents more and leave others unchanged. For this reason, we view our results from expanding federal student loan limits as lower bounds.

ture the fact that the mean and median of private student loan interest rates are roughly the same as federal student loan interest rates, as shown in Table 6. Fourth and finally, to capture the lack of variation in private student loan interest rates along key characteristics (Table 6), we assume lenders cannot price-discriminate by skill or any other characteristic. Consequently, lenders pool each cohort of students to price loans, which leads to a single interest rate, r_{SL}^{pr} (see equation (21) in Supplementary Appendix B.2).[28]

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

3.2 Consumer life cycle problem

This section presents the main value functions; remaining value functions are presented in Supplementary Appendix B.1. Let $e \in \{h, \ell\}$ denote education status where h refers to a high-education consumer who either is enrolled in college or is a college graduate, and ℓ refers to a low-education consumer who did not go to college or who dropped out of college. Let $a \geq 0$ indicate positive net assets that earn an interest rate r and $a < 0$ indicate federal student loan balances. Furthermore, let $x > 0$ denote the outstanding balance of private student loans.

Consumer problems before college graduation age (j $\leq$ 4) Given their type, (s, η, a), which reports skill, s, idiosyncratic AR(1) productivity, η, and net assets, a, an 18-year-old (age $j = 1$) has a value function given by

$$\begin{aligned} \hat{W}(s, \eta, a) =& q[\max_{\hat{d}_e}(1 - \hat{d}_e)V(j = 1, \ell, s, \eta, a, x = 0) + \hat{d}_e\hat{V}(j = 1, h, s, \eta, a, x = 0)] \\ &+ (1 - q)V(1, \ell, s, \eta, a, x = 0) \end{aligned} \tag{1}$$

With probability q, the consumer may make a discrete college entrance decision by choosing $\hat{d}_e \in \{0, 1\}$, where $V(j = 1, \ell, s, \eta, a, x = 0)$ is the value of not going to college and $\hat{V}(j = 1, h, s, \eta, a, x = 0)$ is the over-optimistic value of going to college. The balance of private student loans, x, is set to 0 because no one has taken out any private student loans at age $j = 1$. With exogenous probability $1 - q$, the consumer does not have the option to enroll and proceeds through life as a low-education worker. The value of not going to college or dropping out for $j \leq 4$ is given

[28] We have one market for private student loans because most loans are co-signed. We could incorporate another market for loans that are not co-signed. These loans would have worse terms than co-signed loans. This would make private loans even more of an imperfect substitute for federal loans. Hence, our model specification likely imposes a lower bound for the welfare changes from the federal loan limit expansion experiment.

by

$$V(j,\ell,s,\eta,a,x) = \max_{c\geq 0,a'} U(c,j,\ell) + \beta\psi_j E_{\eta'|\ell,\eta} V(j+1,\ell,s,\eta',a',x) \tag{2}$$

$$s.t.$$

$$(1+\tau_c)c + a' = y_{j,\ell,s,\eta,a} + a + Tr_j - T(y_{j,\ell,s,\eta,a})$$

$$a' \begin{cases} = a & \text{if } \ a < 0 \\ \geq 0 & \text{otherwise} \end{cases}$$

where c is consumption, a' is next period assets or federal student loans, $U(\cdot)$ is the utility function, β is the discount factor, τ_c is the consumption tax rate, $y_{j,\ell,s,\eta,a}$ is income, Tr_j is accidental bequests, and $T(y)$ is the income tax function. For consumers who drop out of college and therefore solve (2), the stock of any student debt is held fixed at a and x until $j = 5$, at which point they begin repaying the loan. For consumers who never enroll in college, net assets are always weakly positive because student loans are the only form of borrowing. The overly-optimistic value of college for $j = 1, 2, 3$ is given by

$$\hat{V}(j,h,s,\eta,a,x) = \max_{\hat{c}\geq 0,\hat{a}',\hat{x}'} U(c,j,h) \ - \xi_L \mathbb{I}_{a\geq 0 \text{ and } x=0 \text{ and } (\hat{a}'<0 \text{ or } \hat{x}'>0)} - \xi_L^{pr} \mathbb{I}_{x=0 \text{ and } \hat{x}'>0} \tag{3}$$

$$+ \beta\psi_j E_{\eta'|\ell,\eta}\left[\hat{p}(s)\max[\hat{V}(j+1,h,s,\eta',\hat{a}',\hat{x}'), V(j+1,\ell,s,\eta',\hat{a}',\hat{x}')] + (1-\hat{p}(s))V(j+1,\ell,s,\eta',\hat{a}',\hat{x}')\right]$$

$$s.t.$$

$$(1+\tau_c)\hat{c} + \hat{a}' + (1-\theta(s)-\theta^{pr}(s))\kappa = y_{j,h,s,\eta,a} + a + Tr_j - T(y_{j,h,s,\eta,a}) + (\hat{x}' - x)$$

$$\hat{a}' \geq -\bar{A}\left(\tfrac{j}{4}\right)[(1-\theta(s)-\theta^{pr}(s))\kappa + \bar{c}]$$

$$\hat{a}' \leq a \ \text{ if } \ \ a \leq 0$$

$$\hat{x}' - x \in \left[0, [(1-\theta(s)-\theta^{pr}(s))\kappa + \bar{c}] - [\max(-\hat{a}',0) - \max(-a,0)]\right]$$

where $\hat{x}'$ is next period private student loans, ξ_L is the loan search and debt aversion cost of acquiring any student loan and ξ_L^{pr} is the additional cost of acquiring a private student loan.[29] The parameter κ is annual tuition and fees;[30] $\theta(s)$ and $\theta^{pr}(s)$ are the share of tuition and fees paid for by public and private grants given skill, respectively; and $\bar{c}$ is the amount that can be borrowed for room and board expenses while in college.[31] These consumers may choose to drop out after the first year of college, which is captured by the max expression in the continuation value. College

[29]The psychic costs of taking out any student loans can be thought of as mental anguish from completing paperwork, which may be excessively complicated, as noted by Dynarski and Scott-Clayton (2008).

[30]In Supplementary Appendix C.3, we analyze the case where tuition depends on skill. The main results do not change.

[31]Although students can use student loans to finance both room and board expenditure and tuition and fees, room and board is not a mandatory expenditure in our model because most students live off campus, as shown in NCES (2020).

students can borrow from federal student loans, where $\bar{A}$ represents the number of years worth of net tuition and fees plus room and board expenses that the federal student loan limit is sufficient to finance.[32] The last constraint is the limit constraint for private student loans, which requires that the flow amount borrowed from private student loans in a given year must not exceed tuition plus room and board costs net of any financial aid.[33] The overly-optimistic value for the final year of college, when $j = 4$, is presented in equation (14) in Supplementary Appendix B.1. When constructing this value, the post-college continuation value conditional on graduation is based on $E_{\eta'|h,\eta}$ rather than $E_{\eta'|\ell,\eta}$. Furthermore, no endogenous dropout decision will be made in the continuation value because in the next period, the consumer will have graduated from college. The rest of the value function for the final year of college remains unchanged from previous years.

When consumers make the college entrance decision in equation (1), they are overly optimistic and will use the inflated value of college from (3) to compute their expected value. However, consumers learn their true continuation probabilities in the first year of college so that, while enrolled, the consumer's realized consumption-savings and dropout decisions are based on the following value function for $j = 1, 2, 3$:

$$V(j,h,s,\eta,a,x) = \max_{c\geq 0,a',x'} U(c,j,h) - \xi_L \mathbb{I}_{a\geq 0 \text{ and } x=0 \text{ and } (a'<0 \text{ or } x'>0)} - \xi_L^{pr} \mathbb{I}_{x=0 \text{ and } x'>0} + \tag{4}$$
$$\beta\psi_j E_{\eta'|\ell,\eta}\big[p_c(j,s)\max[V(j+1,h,s,\eta',a',x'),V(j+1,\ell,s,\eta',a',x')] + (1-p_c(j,s))V(j+1,\ell,s,\eta',a',x')\big]$$

where the control variables and constraints (omitted for the purpose of exposition) for this value function are the same as in the overly-optimistic value function given by (3), but without the hats. The only difference between this value function and the overly-optimistic value function is that (4) incorporates true probabilities of continuing in each year of college, $p_c(j,s)$, rather than the over-optimistic probability, $\hat{p}(s)$. Again, in the final year of college ($j = 4$), the consumer's value of college will be computed using equation (14) in Supplementary Appendix B.1, with the exception that the consumer will use the true continuation probability rather than the over-optimistic continuation probability.

[32] For example, if $\bar{A}$ is equal to four, then the limit is equal to four years of net tuition and fees, plus room and board. The multiplier $\frac{j}{4}$ is an adjustment for the fact that the cumulative limit increases with each year of college.

[33] In our model, the only benefit of a private loan over a federal loan is that with a private loan, a college enrollee can keep their savings, whereas with a federal loan, a college enrollee must first dissave to borrow. With this feature, our model can generate uptake of only private loans by a small minority of students, a pattern we see in the data (see Table 31 in Supplementary Appendix C.3). Specifically, students from rich families may turn to private loans. This outcome is consistent with an implication of the Expected Family Contribution, where in reality, federal student loan limits are tighter for students from income and wealth rich families, and hence, they may turn to private lenders.

Consumer problems after college graduation age (j > 4) Consumers begin student loan payments the year after college graduation age, regardless of whether or not they complete college.[34] For the remainder of this section, we focus on the parent's problem of choosing between repayment and delinquency and their value of repayment at age $j_f + j_a$, the age at which they make an inter vivos transfer. This parent's value function is given by

$$V(j,e,s,\eta,a,x) = \sum_{s_c} \pi(s_c|e)[\max_{d_f,d_x}(1-d_f)(1-d_x)V^R(j,e,s,\eta,a,x,s_c)+ \tag{5}$$
$$d_f(1-d_x)V^{D_f}(j,e,s,\eta,a,x,s_c)+(1-d_f)d_xV^{D_x}(j,e,s,\eta,a,x,s_c)+d_fd_xV^D(j,e,s,\eta,a,x,s_c)],$$

where $\pi(s_c|e)$ is the conditional distribution over child skill given parental education level, and $d_f \in \{0,1\}$ and $d_x \in \{0,1\}$ denote the federal and private student loan delinquency decisions, respectively. The terms $V^R(\cdot)$, $V^{D_f}(\cdot)$, $V^{D_x}(\cdot)$, and $V^D(\cdot)$ denote the value of repayment on both loans, the value of delinquency on only federal loans, the value of delinquency on only private loans, and the value of delinquency on both types of loans, respectively. The value of repayment for $j = j_f + j_a$ is given by

$$V^R(j,e,s,\eta,a,x,s_c) = \max_{c\geq 0,a',b} U(c,j,e) + \beta\psi_j E_{\eta'|e,\eta}V(j+1,e,s,\eta',a',x')+ \tag{6}$$
$$\beta_c E_{\eta'|\ell}\hat{W}(s_c,\eta',b)$$
$$s.t.$$
$$(1+\tau_c)c + a' + b = y_{j,e,s,\eta,a} + a + \mathbb{I}_{\{a<0\}}r_{SL}a + Tr_j - T(y_{j,e,s,\eta,a}) - \rho_R^{pr}(j,x)$$
$$a' \begin{cases} = (1+r_{SL})a + \rho_R(j,a) & \text{if } a < 0 \\ \geq 0 & \text{if } a \geq 0 \text{ and } x = 0 \\ = 0 & \text{otherwise } (a \geq 0 \text{ and } x > 0) \end{cases}$$
$$x' = x(1+r_{SL}^{pr}) - \rho_R^{pr}(j,x)$$
$$b \begin{cases} = 0 & \text{if } a < 0 \text{ or } x > 0 \\ \geq 0 & \text{otherwise } (a \geq 0 \text{ and } x = 0) \end{cases}$$

where b is the inter vivos transfer to the child, $\hat{W}(\cdot)$ is the child's value function, and β_c disciplines the intensity of parental altruism toward the child. Because the parent uses $\hat{W}(\cdot)$ for their child's lifetime utility, the parent is also overly optimistic about the likelihood of their child's college continuation. The child's AR(1) productivity η' is drawn from the stationary distribution for a

[34] In the United States, federal student loans typically have a six-month grace period after graduation in which repayment does not need to be made. Since our model period is one year, we assume that repayment starts at $j = 5$, right after graduation. For simplicity, we assume that payments begin in the same age for dropouts.

consumer without a college degree. The objects $\rho_R(j,a)$ and $\rho_R^{pr}(j,x)$ are full payment functions for federal and private student loans, respectively. If this parent has outstanding federal loans (i.e., $a<0$), then $a' = a(1+r_{SL})+\rho_R(j,a)$. As in Ionescu and Simpson (2016), we assume consumers cannot choose to pay down their federal or private loans faster than the required payment amount. If the parent has paid off their student loans, then they may save and make an inter vivos transfer to their child. [35]

The definition of the equilibrium and the computational algorithm are provided in Supplementary Appendix B.2 and B.3, respectively.

3.3 Functional forms

College continuation probability The true probability of continuing to the next year of college, $p_c(j,s)$, is determined by two objects, $p(s)$ and $\rho_d(s)$, both of which depend on skill:

$$p_c(j,s) = 1-(1-p(s))\rho_d(s)^{j-1} \tag{7}$$

Equation 7 implies that the exogenous dropout probability is $(1-p(s))\rho_d(s)^{j-1}$. The object $p(s)$ determines the common probability of continuing in college in any year of enrollment, while the object $\rho_d(s)$ determines the persistence of the exogenous drop out probability.

Student loan payments The full payment function $\rho_R(j,a)$ for federal student loans is given by

$$\rho_R(j,a) = \begin{cases} -\dfrac{r_{SL}}{1-(1+r_{SL})^{-(T_{SL}+5-j)}}a & \text{if } a<0 \text{ and } 4<j\leq T_{SL}+4 \\ -(1+r_{SL})a & \text{if } a<0 \text{ and } j>T_{SL}+4 \\ 0 & \text{otherwise } (a\geq 0) \end{cases} \tag{8}$$

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

$$\rho_D(j,a,y) = \min[\tau_g \max[y-T(y)-\bar{y},0], \rho_R(j,a)] \tag{9}$$

[35] In the initial stationary equilibrium, the situation where a parent cannot make an inter vivos transfer due to outstanding student loans is rare: only 0.3 percent of consumers at j_f+j_a have student loans.

where the garnishment amount is bounded above at the full payment amount $\rho_R(j,a)$. The payment structure for private student loans is the same as the payment structure for federal student loans with the full payment function, $\rho_R^{pr}(j,x)$, and the partial payment function, $\rho_D^{pr}(j,x,y)$, defined analogously.

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

$$U(c,j,e) = \frac{\left(\frac{c}{1+\zeta\,\mathbb{I}_{j\in\{j_f,..,j_f+j_a-1\}}}\right)^{1-\sigma}}{1-\sigma} - \lambda\mathbb{I}_{e=h \text{ and } j\in\{1,2,3,4\}} \tag{10}$$

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

Income Age, education, skill, an AR(1) earnings productivity, and net assets, summarized by the tuple (j,e,s,η,a), determine income, y, given by

$$\begin{aligned} y_{j,e,s,\eta,a} =& w[\epsilon_{j,\ell,s}\ell_{pt}\mathbb{I}_{j\le 4 \text{ and } e=h} + \epsilon_{j,e,s}\mathbb{I}_{j<j_r \text{ and } (j>4 \text{ or } e=\ell)}]\eta + ss_{e,s}\mathbb{I}_{j\ge j_r} + \\ & r\left[a\mathbb{I}_{j>1 \text{ and } a>0} + Tr_j\right] \end{aligned} \tag{11}$$

where w is the wage rate, $\epsilon_{j,e,s}$ is a deterministic life cycle productivity that depends on age, completed education, and skill, ℓ_{pt} is part-time hours, and $ss_{e,s}$ is the Social Security transfer that depends on completed education and skill (see equation (22) in Supplementary Appendix B.2).[36]

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

$$T(y) = y - \gamma y^{1-\tau_p} \tag{12}$$

where τ_p governs the tax progressivity and γ is used to balance the government budget constraint in every period (see equation (24) in Supplementary Appendix B.2).

Technology The production function is Cobb-Douglas, given by

$$K^\alpha (ZL)^{1-\alpha} \tag{13}$$

[36]The indicator $\mathbb{I}_{j>1 \text{ and } a>0}$ implies that interest income on the inter vivos transfer accrues to the parents and not the consumer at age $j = 1$.

where K is aggregate capital stock, Z is aggregate labor productivity, L is total efficiency units of labor, and α is the capital share. The capital stock depreciates at rate δ.

4 Model Parameterization

The parameters of this model are divided into those estimated outside of the model, shown in Tables 7 and 8, and those calibrated inside of the model, shown in Table 9.

Table 7 presents externally estimated parameters related to education. Panel A begins with parameters governing the federal student loan program: first, the aggregate federal student loan limit, $\bar{A}$, is set to the current cumulative borrowing limit for four years of college, normalized by the average annual net tuition and fees plus room and board based on Smole (2019) and NCES (2019);[37] second, the add-on for the federal student loan interest rate, τ_{SL}, is set to the most recent value of 2.1 percentage points (Chief Operating Officer for Federal Student Aid (FSA), 2021); third, the number of years for repayment on a student loan, T_{SL}, is set to 10 based on Smole (2019);[38] fourth, the garnishment rate conditional on delinquency for both federal and private student loans, τ_g, is set to 15 percent, as reported in Yannelis (2020);[39] and, fifth, the student loan collection fee, ϕ_D, is set to 0.185 following Luo and Mongey (2019). The last row of Panel A reports working hours while in college, ℓ_{pt}, set to the average weekly time spent working for third-year college students in the HSLS:09, expressed as a fraction of full-time work (see Table 25 in Supplementary Appendix A.3).

Panel B of Table 7 reports the estimated share of tuition and fees paid with grants and scholarships from public sources, $\theta(s)$, and private sources, $\theta^{pr}(s)$. To assign these values, in the HSLS:09 we first compute shares of tuition and fees subsidized via grants from any source by skill quantile. Next, we multiply the total share of tuition subsidized by grants by 0.7 to assign values to $\theta(s)$ and assign the residual to $\theta^{pr}(s)$, incorporating estimates from Krueger and Ludwig (2016) on grants from public versus private sources. Panel C of Table 7 reports the conditional distribution of child skill given parental education, $\pi(s_c|e)$. Note that the parameterized model reflects the fact that, in the HSLS:09, parent education and child high school GPA are positively correlated. Panels B and

[37] This limit has been in place since July 1, 2012. The U.S. federal student loan program sets yearly limits and lifetime limits on borrowing. Yearly limits depend on one's academic year (e.g., freshman) and dependency status. We assume borrowers are dependents, and use the cumulative limit over the first four years because college in our model lasts for four years.

[38] In the U.S., those with student loans may choose between a standard repayment plan of 10 years and an income-based repayment plan, which may have a repayment time frame ranging from 10 to 25 years.

[39] We set the garnishment rate for private loans equal to the garnishment rate for federal loans. This is consistent with the U.S. system, where garnishment is allowed for delinquent private loans as long as the loan provider obtains a court order.

Table 7: Externally estimated parameters related to education

Symbol	Parameter description	Data source	Parameter value
Panel A: Federal student loan program and college working hours			
$\bar{A}$	Limit	Smole (2019) and NCES (2019)	1.493
τ_{SL}	Interest rate add-on	Chief Operating Officer for FSA (2021)	0.021
T_{SL}	Maximum years to repay	Smole (2019)	10
τ_g	Federal SL garnishment rate	Yannelis (2020)	0.150
ϕ_D	Student loan collection fee	Luo and Mongey (2019)	0.185
ℓ_{pt}	Working hours while in college	HSLS:09	0.347
Panel B: Grant tuition subsidies, by skill endowment s			$(\ s_1\ ,\ s_2\ ,\ s_3\ )$
$\theta(s)$	Public tuition subsidy	HSLS:09 and Krueger and Ludwig (2016)	(0.285, 0.323, 0.364)
$\theta^{pr}(s)$	Private tuition subsidy		(0.122, 0.139, 0.156)
Panel C: Child skill distribution given parent education, by child skill endowment s_c			$(\ s_{c,1}\ ,\ s_{c,2}\ ,\ s_{c,3}\ )$
$\pi(s_c\|e=\ell)$	Parent does not have BA	HSLS:09	(0.426, 0.341, 0.233)
$\pi(s_c\|e=h)$	Parent has BA		(0.176, 0.311, 0.512)

Notes: Table 7 reports externally estimated parameters. Panel A reports the policy parameters of the federal student loan program and time spent working while in college. Panel B reports the proportional tuition subsidy rates from public and private sources (i.e., grants and scholarships) by skill s. Panel C reports the conditional probability of drawing child skill s_c (high school GPA) given parental education e. Data sources are provided in the second column and moment construction is described in the main text.

C draw on HSLS:09 findings reported in Table 24 of Supplementary Appendix A.3.

Table 8 presents externally estimated parameters unrelated to education. Panel A governs demographics: the fertility period, j_f, is set to 13 so that consumers have a child when they turn 30; the age adulthood begins, j_a, is set to 18; j_r is chosen so that the retirement age is 65; and, finally, J sets maximum life span to 100 years. For $j < j_f + j_a$, we set survival probabilities ψ_j to one to rule out children without parents; ages $j \geq j_f + j_a$ use estimates from Bell and Miller (2020). Panel B, which covers preferences and technologies, begins with the relative risk aversion parameter, σ, set to 2 based on Chetty (2006). The adult equivalence scale, ζ, is set to 0.3 following the Organization for Economic Co-operation and Development (OECD) modified scale. The capital share parameter, α, is set to 0.36 following Kydland and Prescott (1982). The depreciation rate of capital, δ, is set to 0.076, as in Krueger and Ludwig (2016). Life cycle productivities $\epsilon_{j,e,s}$, are estimated and reported in Table 21, Supplementary Appendix A.2.[40] Panel C contains government policy parameters: the consumption tax rate τ_c is set to 5 percent (Krueger and Ludwig, 2016), the progressivity of the income tax function, τ_p, is set to 0.181 (Heathcote, Storesletten, and Violante, 2017), and government consumption as a share of GDP, g, is set to 0.141 using estimates from the Bureau of Economic Analysis (BEA) in BEA (2022a) and BEA (2022b).

Table 9 reports internally calibrated parameters.[41] The first column contains the parameter symbol;

[40] Table 27 in Supplementary Appendix C.1 shows that untargeted within-skill level college wage premiums in the model using these estimated earnings processes align well with their empirical counterparts.

[41] Although parameters and moments are grouped in Table 9 using the most significant one-to-one relationship between

Table 8: Externally estimated parameters not related to education

Panel	Parameter	Description	Data Target	Value
A: Demographics	j_f	Child bearing age	30 years	13
	j_a	Years for child to move out	18 years	18
	j_r	Retirement age	65 years	48
	J	Maximum life span	100 years	83
	ψ_j	Survival probability	Bell and Miller (2020)	-
B: Preferences & technology	σ	Risk aversion	Chetty (2006)	2
	ζ	Adult equivalence scale	OECD modified scale	0.3
	α	Capital share	Kydland and Prescott (1982)	0.360
	δ	Depreciation rate	Krueger and Ludwig (2016)	0.076
	$\epsilon_{j,e,s}$	Earnings life cycle profile	Table 21	-
C: Government	τ_c	Consumption tax rate	Krueger and Ludwig (2016)	0.050
	τ_p	Income tax progressivity	Heathcote et al. (2017)	0.181
	g	Government consumption	BEA (2022a) and BEA (2022b)	0.141

Notes: Table 8 contains externally estimated parameters unrelated to education. Panel A covers demographics; Panel B covers preferences and technology; and Panel C covers the government.

the second column, the parameter description; and the third column, the parameter value. Columns 4 through 6 contain the target moment's description, the moment in the data, and the moment in the calibrated model, respectively. Panel A of Table 9 presents parameters governed by moments from the HSLS:09. The first two objects are $p(s)$, the true continuation probability, and $\rho_d(s)$, the persistence of the true dropout probability. These objects are governed by persistence rates to the end of the third academic year (Y3), given enrollment in a four-year degree (Y1) and persistence to the end of the third academic year conditional on persisting to the second academic year (Y2), respectively (Table 24, Supplementary Appendix A.3). The last two rows in Panel A contain the fixed costs that generate credit market frictions, ξ_L and ξ_L^{pr}, for any student debt and the particular cost of taking out a private loan, respectively. The values of ξ_L and ξ_L^{pr} are set so that the model matches the share of 2013 enrollees that have any student debt and the share with positive private student loan balances after completing their third academic year, respectively (Table 4).[42]

Panel B of Table 9 reports parameters that are governed by moments from the NLSY97. The college effort cost net of the consumption value of college, λ, is determined by observed college enrollment rates by age 25; the college enrollment option shock, q, is chosen to target the enrollment rate of the top skill quantile (Tables 13 and 14, Supplementary Appendix A.1). The parameter β_c, the degree of a parent's altruism toward their child, is set so that the model matches average parent-to-child transfers (Table 19, Supplementary Appendix A.1), where the normalizing GDP per capita for those 18 and over covers 2016-2018 from BEA (2022a). Lastly, $\hat{p}(s)$ is a vector

each parameter and target moment, and are discussed accordingly, the parameters are calibrated jointly and each parameter can affect all target moments.

[42] Even with a value of 0 for ξ_L, the model somewhat understates the overall student loan uptake rate. In Table 31 in Supplementary Appendix C.3, we compare the student loan portfolio in the model with its data counterpart, and also consider an alternative calibration where we choose ξ_L^{pr} to target the share of students with only private loans.

Table 9: Internally calibrated parameters

Symbol	Parameter description	Parameter value	Moment description	Data moment	Model moment
Panel A: Moments from the HSLS:09					
$p(s)$	Continuation probability	(0.615,0.823,0.906)	Persist to Y3 | Y1	*(0.476,0.711,0.829)*	*(0.476,0.711,0.829)*
$\rho_d(s)$	Dropout prob. persistence	(0.586,0.772,0.908)	Persist to Y3 | Y2	*(0.774,0.863,0.913)*	*(0.774,0.863,0.915)*
ξ_L	Loan search cost	0.000	Loan uptake	*0.650*	*0.562*
ξ_L^{pr}	Private loan uptake cost	2.713	Private loan uptake	*0.220*	*0.220*
Panel B: Moments from the NLSY97					
λ	Net college effort cost	0.133	Enr. by age 25	*0.478*	*0.478*
q	Enrollment option shock	0.770	Enr. by age 25 | s_3	*0.770*	*0.770*
β_c	Parent altruism toward child	0.198	$\frac{\text{Average transfer}}{\text{GDP pc 18+}}$	*0.578*	*0.578*
$\hat{p}(s)$	Exp. continuation prob.	(0.951,0.967,0.983)	Exp. graduation rate	*(0.818,0.874,0.936)*	*(0.818,0.874,0.936)*
Panel C: Moments from other sources					
$\bar{c}$	College room and board	0.147	$\frac{\text{Average room + board}}{\text{GDP pc 18+}}$	*0.147*	*0.147*
κ	Annual tuition	0.171	Net tuition + fees	*0.088*	*0.088*
$\bar{y}$	Garnishment-exempt income	0.151	$\frac{\text{Exempt earnings}}{\text{GDP pc 18+}}$	*0.151*	*0.151*
ξ_D	Federal delinquency cost	0.168	Delinquency rate	*0.090*	*0.091*
ξ_D^{pr}	Private delinquency cost	1.207	$\frac{\text{Delinquent private debt}}{\text{Private debt in repayment}}$	*0.074*	*0.075*
τ_{is}	Student loan issuance cost	0.040	Rate comparison	-	*0.065*
Z	Aggregate labor productivity	0.308	GDP per capita 18+	*1.000*	*1.000*
β	Discount factor	0.972	Capital-to-output ratio	*3.000*	*3.000*
χ	SS replacement rate	0.187	$\frac{\text{SS expenditure}}{\text{GDP}}$	*0.048*	*0.048*

Notes: Table 9 presents internally calibrated parameters related to education: Panel A parameters use HSLS:09 moments; Panel B parameters use NLSY97 moments; Panel C reports parameters governed by other sources. Data sources and moment construction are described in the text.

of expected yearly continuation probabilities, whose values are chosen to align the implied expectations about graduation likelihood in the model with the data (Table 1). The difference between the vector of expected continuation probabilities, $\hat{p}(s)$, and the vector of true continuation probabilities, $p_c(j,s)$, determines the extent of over-optimism in our model for each skill quantile s in academic year j.[43]

Panel C of Table 9 contains parameter governed by moments from other sources. College room and board costs, $\bar{c}$, is set using the average annual value for room and board at bachelor's programs, and annual tuition, κ, targets average net tuition and fees for 2016-2018 as reported in NCES (2019), normalized with GDP per capita for those 18 and over during the same period. The

[43]The evidence in Table 2 indicates that in the NLSY97 the expected probability of earning a bachelor's degree positively predicts college enrollment, even conditioning for skill (high school GPA). Our model abstracts from belief heterogeneity within skill quantiles. This does not affect the conclusions we draw about the role of over-optimism in the economy, because the beliefs of those not enrolled in the baseline do not matter for that experiment. However, assumptions about the beliefs of those who do not enroll may affect the welfare implications of a federal loan limit expansion in the presence of over-optimism, as studied in our second experiment. To examine the extent to which this is the case, in Supplementary Appendix C.3 we perform a robustness exercise where we calibrate the model to the beliefs of non-enrollees observed in the NLSY97. We view over-optimism for this group as a lower bound on the extent of over-optimism in the population. Our main results on the effects of loan limit expansion are robust to belief heterogeneity within skill quantiles.

income exempt from garnishment in delinquency, $\bar{y}$, is set to 15.1 percent of GDP per capita for the population 18 and over, based on our calculations using results from Yannelis (2020). The parameter governing the costs of being delinquent on public loans, ξ_D, is set so that the model's delinquency rate matches the average cohort delinquency rate from 2016 to 2018 reported in FSA (2021b), where the definition of delinquency in the data is a delay in payment of 270 days or more. The delinquency cost for private loans, ξ_D^{pr}, is set so that the model matches private loan balances 90 or more days delinquent as a fraction of total private loan balances for 2016-2018 as reported in Amir, Teslow, and Borders (2021).[44] The student loan issuance cost, τ_{is}, is set so that the interest rates of federal and private student loans have the same mean, as documented in Table 6 (see equations 21 and 24 in Supplementary Appendix B.2). Aggregate labor productivity, Z, is set so that GDP per capita for the population 18 and over is 1 in the model. The discount factor, β, is calibrated to target a capital-to-output ratio of 3, consistent with Jones (2016). Finally, the Social Security replacement rate, χ, targets the average ratio of total Social Security expenditure to GDP from 2016 to 2018, as measured by the Bureau of Economic Analysis in BEA (2022c) and BEA (2022a).

5 Properties of the Initial Stationary Equilibrium

This section presents properties of the initial stationary equilibrium that are related to our main experiments. Subsection 5.1 examines over-optimism's effects on consumer choices, focusing on its role in generating observed enrollment patterns and the extent of over-enrollment.[45] In Subsection 5.2, we examine federal student loan limit utilization rates in both the data and the model.

5.1 Over-optimism's effects on enrollment choices

Column (1) of Table 10 reports enrollment rates for each skill quantile in the NLSY97, while column (2) reports enrollment rates in the model's calibrated baseline equilibrium.[46] Moments from the model align closely with the data because we target the overall college enrollment rate and the enrollment rate in the top skill quantile in the model calibration. Column (3) of Table 10 reports counterfactual enrollment rates for the same distribution of high school graduates as in the initial stationary equilibrium when we shut off over-optimism by setting $\hat{p}(s) = p_c(j, s)$.

[44] For federal student loans, after 270 days spent in delinquency, the loan is in default. Since the model period is one year, we use the cohort default rate (270 or more days delinquent) as the empirical target for the per-period delinquency rate. For private loans, we use the available delinquency definition (90 or more days) closest to the length of a period in our model when selecting the empirical target.

[45] In Supplementary Appendix C.1, we examine over-optimism's effects on borrowing behavior and family transfers.

[46] NLSY97 enrollment estimation details are reported in Table 13 of Supplementary Appendix A.1.

This is a partial equilibrium statistic where we do not allow general equilibrium objects to adjust. Without over-optimism, enrollment rates decrease, especially among low-skill 18-year-olds. We define the difference between enrollment rates in columns (2) and (3), reported in column (4), as the over-enrollment in that skill quantile.

Table 10: College enrollment statistics by skill quantile

Statistic:	**College enrollment rate**			**Level of over-enrollment**	**Share over-enrolled**	
Sample:	**High school graduates**			**High school graduates**	**College enrollees**	
Skill	**(1) Data**	**(2) Baseline**	**(3) No over-optimism**	**(4) = (2) - (3)**	**(5) Data**	**(6) = 100 * (4) / (2)**
1	22.92	25.10	9.33	15.77	69.40	62.83
2	45.57	44.35	38.77	5.57	28.45	12.57
3	77.01	77.01	77.01	0.00	10.09	0.00

Notes: Table 10 presents enrollment statistics in the data and model by skill quantile, where skill quantile is assigned with high school GPA in the data and represented with s in the model. Enrollment rates are computed after high school graduation as percentages of the skill quantile's population who enroll in a BA program. Columns (1), (2), and (3) report the enrollment rates in the data, in the initial stationary equilibrium of the model, and when $\hat{p}(s) = p_c(j, s)$, so that there is no over-optimism and consumers have correct beliefs, but general equilibrium objects are not allowed to adjust; column (4) reports the level of over-enrollment, computed as the difference between columns (2) and (3) in units of percentage points. Columns (5) and (6) report the share of college students over-enrolled within each skill quantile, for the NLSY97 and in the baseline model, respectively.

Although we cannot exactly predict the extent of over-enrollment in the data, we use the findings reported in model (1) of Table 2 to compute how enrollment would change for the sample of enrollees in the NLSY97 if they had the "correct" beliefs, where correct beliefs correspond to the true graduation likelihood for each skill quantile; the share of college enrollees who would not enroll with correct beliefs in the data is reported in column (5).[47] Column (6) reports the share of over-enrollment among enrollees in the model's initial stationary equilibrium. Although not targeted, over-enrollment computed in the model aligns closely with its approximated empirical counterpart.

5.2 Federal student loan limit utilization rates

The current federal student loan limit is enough to pay for 1.49 years of average total college expenses at a four-year college, net of grants, if we include the average expenditure for college room and board. The model is calibrated to match this attribute of current federal loan policy. To what extent are college students using all of the federal loans to which they have access? To measure utilization rates in the data, we turn to the HSLS:09.[48] We compute the federal loan

[47] See Table 18 in Supplementary Appendix A.1 for details.

[48] To apply for federal aid, college students submit the Free Application for Federal Student Aid (FAFSA). On this form, students select a dependency status; dependency status determines annual borrowing limits for federal student loans. The public version of the HSLS:09 does not report which dependency status each FAFSA filer selects. We

utilization rate for college enrollees who persist for three academic years after enrollment, where the utilization rate is the ratio of the cumulative federal debt balance to cumulative borrowing limits after the first three years of college (in 2016). The results are reported in Table 11: 54 percent of those who completed their third academic year utilized more than half of their cumulative federal student loan limit, 34 percent utilized more than 90 percent, and 28 percent utilized all of their available federal loans. Although these moments are not targeted in the calibration, Table 11 indicates that the model's baseline equilibrium also exhibits a sizable share of students using all of their available federal loans. Because we underestimate this share in the model baseline, our welfare estimates from loan expansions can be considered lower bounds.

Table 11: Utilization rates for federal student loans

Utilization	**Data**	**Model**
$\geq 50\%$	54	40
≥ 90 %	34	18
$\geq 100\%$	28	16
Obs	1,855	

Notes: Table 11 reports utilization rates for federal student loans in the HSLS:09 and in the baseline model equilibrium. The empirical moments are estimated for students who enrolled in a BA program in the fall of 2013 and persisted to the end of their third academic year. Utilization rates of federal student loans are computed at the end of the students' third academic year, expressed as percentages of the cumulative limit up to that point (the sum of annual limits for the first three academic years). Weights are PETS-SR student records longitudinal weights. Data source: HSLS:09.

6 Main Experiments

This section presents and discusses the results of our two main experiments. Subsection 6.1 examines the macroeconomic and welfare impact of over-optimism about college graduation in general equilibrium by setting $\hat{p}(s) = p_c(j, s)$. In Subsection 6.2, we analyze the effects of expanding the federal student loan limit to $\bar{A} = 4$, so that federal loans are sufficient to pay for four years of college tuition, net of grants, plus room and board. This expansion allows overly-optimistic high school graduates to access more credit if they enroll in college, potentially worsening over-enrollment, but also relaxes a binding constraint. Therefore, the welfare consequences of a federal student loan limit expansion are ex-ante ambiguous, with the parameterized model determining the relative magnitudes of each of these forces. In both exercises, we assume that the economy is in its

assume everyone files as dependents because most undergraduate students (and all students in the HSLS:09 in 2016, the year in which we measure their utilization rates) are less than 24 years old. Besides age, other ways to be classified as independent are to be married, follow a graduate program, serve on active duty in the U.S. armed forces or be a veteran, have dependent children, have deceased parents, be an emancipated minor, or be determined as an unaccompanied minor (FSA, 2022b). Most undergraduate students do not satisfy these criteria.

steady state in period 0. In period 1, the transition is announced unexpectedly, but there is perfect foresight thereafter.

Welfare We focus on 18-year-old consumers and use consumption-equivalent variation as our welfare measure. We compute the lifetime change in consumption required in the initial steady state value of not going to college, in every period and at every state, in order for an 18-year-old to be indifferent between the initial steady state value of not going to college and the lifetime value before going to college in the initial steady state, the transition path, or the final steady state.[49] We assume that the social planner is altruistic and has correct beliefs ("paternalistic government"); this planner knows the true payoff of choices but internalizes that the consumer is overly optimistic when making the college enrollment decision, the inter vivos transfer decision, and the decisions leading up to and including the age at which the inter vivos transfer is made. The value functions and equations used to construct welfare estimates are provided in Supplementary Appendix B.4. We report the change in lifetime consumption relative to period 0, when the economy is at the initial steady state. Therefore, positive values indicate gains and negative values indicate losses.

6.1 Impact of over-optimism

The effects of eliminating over-optimism on the model's steady state equilibrium are shown in column (1) of Table 12. 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 over-enrollment by skill. By construction, in the new equilibrium over-enrollment—which is the difference between equilibrium enrollment choices and predicted choices made with correct beliefs—goes to zero. That statistic was highest for the lowest-skilled students in the baseline equilibrium, so over-enrollment changes the most for those with the lowest skill. The next row reports changes in college enrollment, which falls for low- and medium-skill 18-year-olds for two reasons. First, when young adults use the true probabilities of college continuation in making their college enrollment decision, the value of going to college decreases to its true value, which is what reduces over-enrollment to zero and causes college enrollment to fall. Second, when parents use the true probabilities of college continuation for their children, the expected return on a college investment decreases, which reduces parental transfers and causes a further fall in college enrollment. The second reason explains why the decrease in college enroll-

[49]Because our model includes utility costs, we follow Abbott, Gallipoli, Meghir, and Violante (2019) and use the value of not going to college, which does not include any psychic costs, in order to compute consumption-equivalent variation.

ment is higher than the decrease in over-enrollment, especially for medium-skill 18-year-olds.[50] The next row of Panel A indicates that the elimination of over-enrollment leads to a higher graduation rate, because the average college student now has higher skill and is therefore more likely to graduate. However, lower enrollment in college leads to fewer college graduates at the new steady state, so that the mass of 18-year-olds with low skill increases and the mass with high skill decreases because skill endowments of children are positively correlated with parental educational attainment in the parameterized model.

Table 12: Steady state changes

Panel	**Variable**	**(1) Elimination of over-optimism**	**(2) Federal loan limit expansion**
A: Education and skill statistics Units: percentage point change	Over-enrollment by s	(-15.77,-5.57,0.00)	(44.34,26.60,0.00)
	College enrollment rate by s	(-20.25,-23.58,0.00)	(46.69,32.66,0.00)
	Graduation rate	5.27	-4.26
	Population share college graduates	-8.54	13.59
	Share of 18-year-olds by s	(2.13,0.25,-2.39)	(-3.40,-0.40,3.80)
B: Macroeconomic aggregates Units: percentage change	Labor (efficiency units)	-3.70	5.86
	Capital	-2.97	0.60
	Output	-3.44	3.94
	Consumption	-3.35	3.55
C: Prices, income tax rate, transfers Units: percentage point/percentage change	Risk-free savings interest rate	-0.07	0.39
	Wage rate	0.35	-1.75
	Private student loan interest rate	-0.23	-
	Income tax rate | Initial ss mean income	0.57	-0.31
	Inter vivos transfers	-26.17	-6.08
	Accidental bequests	-3.24	5.41
	$\mathrm{ss}_{\ell,s}$ by s	(-2.09,-2.07,-2.04)	(2.29,2.25,2.19)
	$\mathrm{ss}_{h,s}$ by s	(-1.63,-1.54,-1.34)	(1.38,1.35,1.14)

Notes: Table 12 provides results from a steady state comparison of the baseline economy to: (1) an economy without over-optimism (i.e., $\hat{p}(s) = p_c(j, s)$) and (2) an economy with a federal student loan limit expansion to fund four years of college tuition plus room and board net of grants (i.e., $\bar{A} = 4$). 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 present as a tuple in the order (s_q, s_2, s_3).

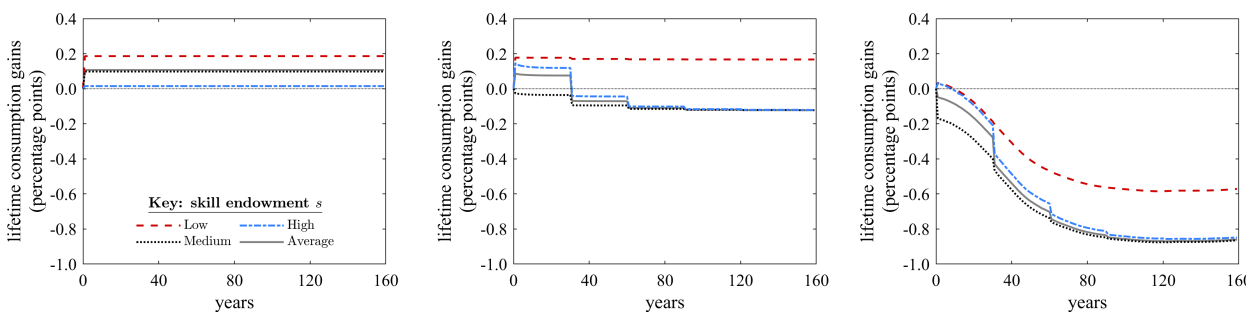
Moving to Panel B, note that the drop in the mass of college graduates reduces the total efficiency units of labor, which reduces total labor earnings. Lower earnings, in turn, lower both savings and aggregate capital. This reduction in factor inputs lowers output and, consequently, lowers consumption. Panel C of Table 12 indicates that the risk-free savings rate falls and the wage rate increases slightly because aggregate labor falls more than aggregate capital. At the same time, lower delinquency risk among private student loan borrowers (which arises because of their higher skill composition) causes the interest rate on private student loans to decrease.

As mentioned above, eliminating over-optimism leads to lower college enrollment because 18-year-olds no longer over-enroll and also because parents reduce transfers. This means that there are fewer college graduates in the economy, and thus fewer high earners, which causes a reduction

[50] A more detailed discussion for the second mechanism is provided in Supplementary Appendix C.2.

in income tax revenue at the initial steady state's tax rate. In the presence of progressive income taxation, the fall in income tax revenue is larger than the fall in government expenditure at the initial steady state tax rate, so that the average income tax rate increases in the new steady state in order to balance the government's budget. This fiscal externality of a college degree is not internalized by consumers: specifically, neither 18-year-olds making the college enrollment decision nor their parents making transfer decisions take into account how these actions affect the average income tax rate. The progressive nature of the income tax system is a key feature of the model environment that introduces this fiscal externality to a college education.[51]

When over-optimism is eliminated, inter vivos transfers decline significantly relative to the baseline economy for three reasons: first, parents' altruistic incentive to provide inter vivos transfers to their children might decrease because parents are no longer overly optimistic about their children's ability to graduate from college; second, the economy will have less wealth and income in the new steady state; and, third, there will be fewer high-skill children, which will lower parents' incentive to invest in college.[52] The last two rows of Panel C show that transfers such as accidental bequests and Social Security also decrease, because of lower savings and lower labor earnings in the new steady state.



(a) PE: exogenous 18 y/o distribution (b) PE: endogenous 18 y/o distribution (c) General equilibrium

Figure 1: Elimination of over-optimism welfare analysis: partial and general equilibrium effects

Notes: Figure 1 provides a welfare analysis of eliminating over-optimism for 18-year-old consumers in partial and general equilibrium. Subfigures 1a-1c report lifetime consumption gains and losses for the average 18-year-old and the average-18-year-old given skill in each period of the transition path under the following cases separately: (a) a partial equilibrium 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; (b) a partial equilibrium in which the income tax rate, prices, bequests, and Social Security transfers are fixed at their initial steady state values, but the 18-year-old distribution is endogenous; and (c) general equilibrium.

[51] In an alternative framework with flat income taxation ($\tau_p = 0$), which is re-calibrated to match the same set of target moments as the baseline model, eliminating over-optimism leads to only a small change in the income tax rate of -0.07 percentage points, as opposed to 0.57 percentage points in the baseline.

[52] See Table 29 in Supplementary Appendix C.1 and surrounding text for further discussion of the first mechanism.

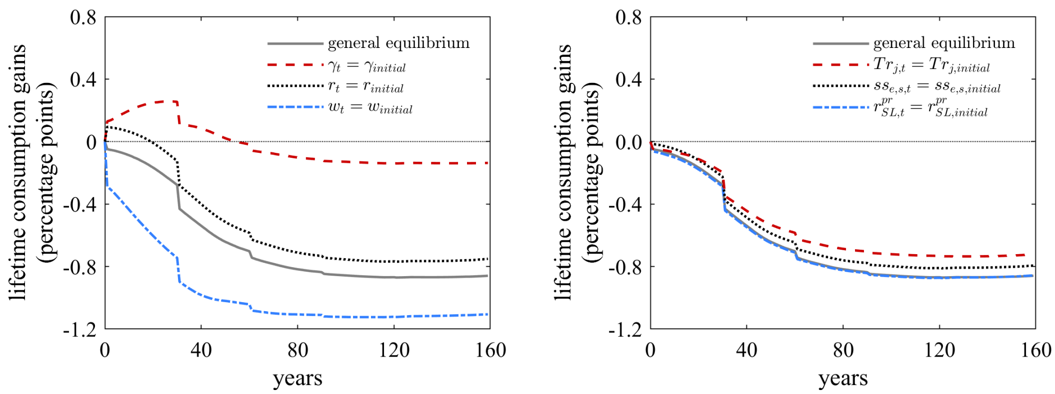
Figure 1 illustrates a welfare analysis of eliminating over-optimism in both partial and general equilibrium for 18-year-old consumers. Subfigure 1a shows welfare changes by skill quantile, and on average, in a partial equilibrium in which the income tax rate, prices, bequests, Social Security transfers, and the 18-year-old joint distribution of assets, skill, and the AR(1) earnings shock are fixed at their initial steady state values. In Subfigure 1a, consumers benefit from having their beliefs corrected in proportion to the extent of over-optimism for their skill endowment. This is the direct impact of eliminating over-optimism: consumers correct their enrollment decisions and the transfers they make later in life as parents, both of which are changes that improve their well-being. Subfigure 1b plots welfare changes in a partial equilibrium that now endogenizes the 18-year-old joint distribution. For the low- and medium-skill, welfare gains in the initial periods of the transition are lower in Subfigure 1b than in Subfigure 1a, because parents with corrected beliefs reduce inter vivos transfers to children; for those with high skill, welfare gains in the initial periods of the transition are larger because parents increase inter vivos transfers (see Table 29 in Supplementary Appendix C.1). In later periods of the transition, however, welfare decreases for all skill levels. This occurs because the population of parents become less educated over time, which lowers parental earnings and wealth and lowers the skill of young adults. Both of these effects compound the fall in inter-vivos transfers. Subfigure 1c indicates that, once we take into account general equilibrium effects, welfare changes become even more negative. This is primarily a result of an increase in the income tax rate, as discussed in the next paragraph.

Figure 2 decomposes welfare changes by attributing them to each of the several objects that adjust in general equilibrium. In Subfigure 2a, we plot lifetime consumption changes during the transition for the following partial equilibrium cases: the income tax level parameter, γ_t, the risk-free savings rate, r_t, and the wage rate, w_t, each fixed at their initial level while other variables adjust in equilibrium. General equilibrium welfare changes are also included for comparison. When the income tax rate is fixed at its initial level, welfare losses for the average 18-year-old are significantly reduced and even become gains in the initial periods of the transition. This result indicates that higher income taxes stemming from eliminating over-optimism are a key driver of welfare losses.[53] A similar pattern, although to a lesser extent, occurs when we hold fixed the risk-free interest rate on savings at its initial level instead of allowing it to fall. By contrast, fixing the wage rate at its initial level magnifies welfare losses for the average 18-year-old consumer, indicating that the equilibrium increases in this object act to mitigate the welfare losses resulting from eliminating over-optimism.

Subfigure 2b plots welfare changes in partial equilibrium when accidental bequests, Social Secu-

[53] As discussed above, progressive income taxation is a key ingredient for the elimination of over-optimism to lead to higher income taxes. In Supplementary Appendix C.3, we analyze welfare implications with flat income taxation: welfare losses are smaller and low skill consumers experience gains.

rity transfers, and private student loan interest rates are fixed at their initial steady state values, respectively. Lower accidental bequests and Social Security transfers hurt the consumer in general equilibrium, since holding these objects fixed lowers welfare losses. The fall in the private student loan interest rate has no significant impact. The magnitudes of the effects in Subfigure 2b are quite small compared to Subfigure 2a.



(a) Part 1 (b) Part 2

Figure 2: Decomposing general equilibrium welfare effects of eliminating over-optimism

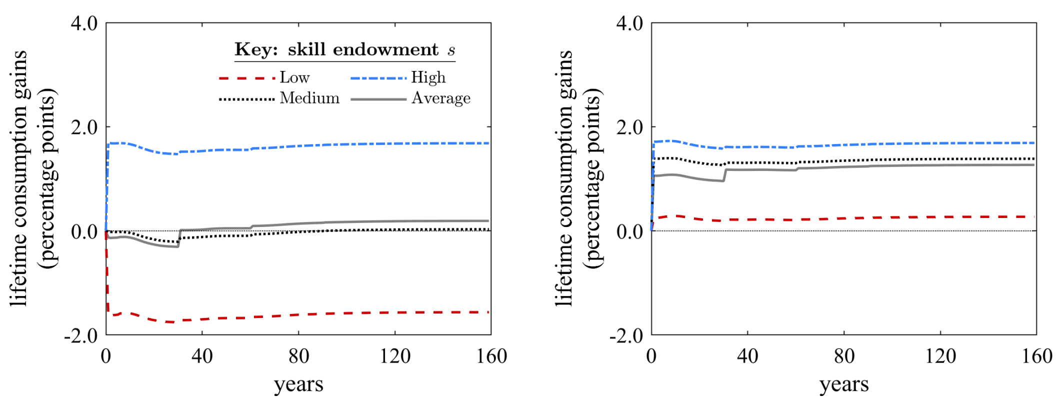
Notes: Figure 2 provides a welfare analysis of eliminating over-optimism for the average 18-year-old consumer to decompose general equilibrium effects. Subfigures 2a and 2b plot lifetime consumption gains and losses for the average 18-year-old in each period of the transition path under the following cases: general equilibrium, income tax level parameter γ_t fixed at its initial level, risk-free savings rate, r_t, fixed at its initial level, wage rate, w_t, fixed at its initial level, accidental bequests, $Tr_{j,t}$, fixed at its initial level, Social Security transfers, $ss_{e,s,t}$, fixed at their initial level, and private student loan interest rate, $r^{pr}_{SL,t}$, fixed at its initial level. For each partial equilibrium case, while the relevant variable is fixed at its initial level, the other variables change as they do in general equilibrium.

To summarize, in general equilibrium the average consumer is better off with over-optimism because everyone is overly optimistic at the same time. The fact that everyone is overly optimistic at the same time is what allows the average income tax to be lower, as well as transfers and skill to be higher, in equilibrium. In such an environment, some groups of consumers drop out of college more often than they expected. Those individuals are still better off than in a world without over optimism, because the aggregate endogenous states are favorable to them (mainly lower income taxes). Of course, if mistaken beliefs of a few individuals are changed, or everyone's beliefs are changed without allowing for parent choices or aggregate quantities to adjust, then young people are better off when they correctly understand their own risks.

6.2 Federal loan limit expansion

The effects of expanding the federal loan limit to $\bar{A} = 4$ on education, skill, and macroeconomic aggregates are shown in column (2) of Table 12. Panel A shows that the expansion in the federal loan limit increases enrollment for the lowest two skill quantiles, which raises over-enrollment for those quantiles. Enrollment increases because young adults previously constrained in their access to federal credit (which has a lower uptake cost compared to private loans) can now access more of it; higher enrollment among low-skill 18-year-olds leads to a lower graduation rate overall. Nevertheless, higher enrollment also increases the share of college graduates in the population, which leads to more 18-year-olds with higher skill endowments in the new steady state. Panel B reports the resulting increase in aggregate labor efficiency units, capital, output, and consumption.

In Panel C, we see that the risk-free interest rate on savings rises and the wage rate drops because efficiency units of labor rise by more than the capital stock. By construction, the private student loan market completely shuts down when students can use federal loans to pay for all college costs, because the borrowing limit on private loans is set as the residual of what can be financed with financial aid. With more college graduates, the income tax base expands; in particular, the mass of high-earners rises. Progressive income taxation allows the average income tax rate to decrease in response. Both public transfers from Social Security and accidental bequests rise, but inter vivos transfers decrease because federal loans are now sufficient for financing college expenses.



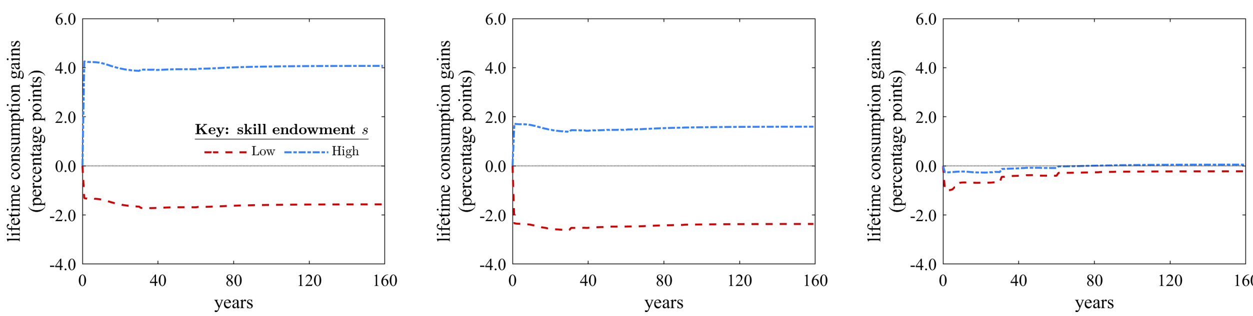
(a) Baseline

(b) No over-optimism

Figure 3: Federal loan limit expansion welfare analysis: baseline versus no over-optimism

Notes: Figure 3 shows a welfare analysis of an expansion in the federal student loan limit to fund four years of college net tuition plus room and board for 18-year-old consumers in the baseline economy (Subfigure 3a) and an economy without over-optimism (Subfigure 3b). Both subfigures report lifetime consumption gains and losses for 18-year-olds, both on average and by skill endowment level, in each period of the transition path.

Figure 3 compares the welfare implications of expanding the federal student loan limit for 18-year-old consumers in the baseline economy with over-optimism (Subfigure 3a) and in an economy without over-optimism (Subfigure 3b), where the latter is re-calibrated to match the same set of target moments as the baseline except for moments related to beliefs about the likelihood of college graduation. In the baseline economy with over-optimism, 18-year-olds with the lowest skill endowment experience welfare losses whereas high-skill 18-year-olds experience welfare gains. Middle skill 18-year-olds are hurt in the initial periods of the transition, albeit slightly. Overall, the average 18-year-old is slightly worse off in the initial periods of the transition and slightly better off in the later periods. By contrast, when we perform the same experiment in an environment without over-optimism, we find that 18-year-olds in all skill quantiles experience welfare gains, which are increasing in skill. When over-optimism is included in the model, welfare losses arise for those with low skill because college enrollment strongly increases for the low skill from poor families when loan limits expand. That is, the policy change worsens over-enrollment for this group. These students drop out of college more often than they anticipate at the time of enrollment.



(a) Family income quantile 1 (b) Family income quantile 2 (c) Family income quantile 3

Figure 4: Federal loan limit expansion welfare analysis: by family income and skill

Notes: Figure 4 provides a welfare analysis of an expansion in the federal student loan limit to fund four years of college net tuition plus room and board for 18-year-old consumers by family income quantile and skill quantile in general equilibrium. Subfigures 4a-4c report lifetime consumption gains and losses for the average-18-year-old in the lowest and highest skill quantiles in each period of the transition path by family income quantiles 1, 2, and 3, respectively.

The U.S. federal student aid program is intended to provide funding that facilitates college attendance for young adults without other forms of financing. Such young adults are primarily from low-income families. In Figure 4, we plot welfare implications of the loan expansion by family income quantile as well as skill. Subfigures 4a and 4b show that 18-year-olds from low-income families in the lowest skill quantile experience large welfare losses, whereas 18-year-olds from low-income families in the highest skill quantile experience large welfare gains. At the same time, the impact of the loan limit expansion on the welfare of 18-year-olds from high-income families is small. This group received large inter vivos transfers from their parents before the policy change, and a higher federal student loan limit simply crowds out family transfers for them without changing their enrollment decisions.

7 Conclusion

In this paper, we document that both students and their parents are overly optimistic about the likelihood of college graduation. We incorporate this feature of the data into a structural model of college enrollment choice, parameterize the model, and use it to perform experiments highlighting the role of over-optimism both in the aggregate economy and in the effects of college financial aid policy. Our analyses lead to two main findings. First, although over-optimism leads 18-year-olds to over-enroll in college, it also benefits these young adults once we consider the impact of general equilibrium adjustments in the average income tax rate, as well as changes in parental transfers and intergenerational effects on skill. Second, in the presence of over-optimism, an expansion in the federal student loan limit leads to welfare losses for low-skill young adults from poor families. This happens because access to more federal student loans worsens over-enrollment in college for these consumers.

While we document and analyze the implications of over-optimism about college graduation, many questions remain for future research. How should student loan repayment policies be designed in the presence of this over-optimism? To what extent should federal student loan limits depend on student attributes? We hope that our empirical findings and quantitative analysis will be useful for future researchers seeking to answer such questions about policy design.

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Online appendix for "Over-optimism About Graduation and College Financial Aid". Not for publication.

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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, U.S. Department of Labor, 2019). This survey collected data annually from 1997 to 2011 and biannually from 2011 to the present (rounds 1 through 19).

Educational attainment outcomes versus expectations Table 13 reports enrollment rates by age 25 and by age 30 in the NLSY97 for each skill quantile, assigned using the distribution of high school GPA among high school graduates. These enrollment rates are very similar; most enrollment happens before age 25. We use enrollment by age 30 to compute over-optimism because this aligns with the wording of the expectations question in the NLSY97 questionnaire. For the enrollment rates used as calibration targetsl, enrollment by age 30 is not an intuitive mapping to the one-time enrollment choice consumers make at age 18 in the model. Since the model allows this choice to be made once immediately after high school graduation, but in reality young people may wait a few years after high school before enrolling in college, using enrollment by age 18 in the data is not satisfactory either. We therefore use enrollment by age 25, between these two ages, as the calibration target.

Table 13: Bachelor's degree program enrollment rates by skill quantile and overall

Skill	Group obs	Enrolled by age 25	Enrolled by age 30
1	807	22.92	27.51
2	812	45.57	48.65
3	748	77.01	78.48
Total	2,367	47.78	50.87

Notes: Table 13 shows enrollment rates in a 4-year degree program by age 25 and by age 30, for each skill quantile. Skill quantiles are assigned using the distribution among high school graduates. Enrollment rates computed for the same sample. Source: NLSY97.

Table 14 shows enrollment rates by age 25 broken down by family income quantile in addition to skill quantile. Family income quantiles are assigned using the distribution of high school graduates; note that the sample with valid family income observations is smaller than the main high school graduates sample. These enrollment rates are used to calibrate a sensitivity analysis in Subsection

C.3, where the college enrollment option shock, q, depends on skill.

Table 14: Bachelor's degree program enrollment rates by skill and family income quantile

Income:	**1**		**2**		**3**	
Skill	**Enr. rate**	**Obs**	**Enr. rate**	**Obs**	**Enr. rate**	**Obs**
1	19	242	22	190	32	148
2	27	204	48	198	66	173
3	64	116	72	196	88	248
Obs	1,715					

Notes: Table 14 reports the enrollment rate in 4-year program by age 25, by skill (rows) and family income (columns) quantile. Enrollment rates are in percentages. Sample is high school graduates for whom family income is also observed. Source: NLSY97.

Table 15 reports the difference between student and parent expected probabilities of obtaining a BA, within the same family, when both expectations are reported (parent beliefs are only reported with valid responses for a subset of the student beliefs sample). The average expected probabilities of parents and children in the same family agree within a few percentage points of each; the median difference is 0. Percentiles of the distribution of differences other than the median (p50) are also reported in the table and indicate the the distribution is largely symmetric around 0. These results support our modeling assumption that parents are overly optimisc to the same extent as their children.

Table 15: Moments of the distribution of within-family difference in beliefs

Skill	**Group obs**	**mean**	**p10**	**p25**	**p50**	**p75**	**p90**
1	166	0.99	-40	-10	0	20	40
2	297	2.09	-25	-1	0	15	28
3	429	0.31	-15	-5	0	0	20
Obs	892						

Notes: Table 15 shows statistics on the distribution of within-family differences between parent and child expected probabilities of the child earning a BA. Sample: students who enrolled in a BA program before age 30, whose parents responded to the beliefs question. Source: NLSY97.

In Table 16 we report the graduation rate, expected graduation rate, and implied over-optimism by gender and student skill quantile (Panel A) and by parental education and student skill quantile (Panel B).[54] In Panel A, we see that the difference across genders within each skill bin is small. In Panel B, we see that parental education is more predictive of over-optimism than gender (note that parental education is defined at the family level where having at least one parent with a BA or more is "High"; otherwise, the family is a "Low" education family). Within a skill bin, low

[54] Note that, as in the main text, we assume throughout that the expected probability of enrollment is 1, so that reported probabilities are interpreted as the conditional probability of graduating once enrolled. Relaxing this assumption would raise measured over-optimism with respect to college persistence probability.

education families tend to be more overly optimistic than high education families. Nevertheless, within a skill bin, we see more similarity across education categories than across skill bins within an education category.

Table 16: Over-optimism about BA attainment: breakdowns

Panel A: by student gender and skill	**Gender**	**Skill**	**Obs**	**Earned BA by age 30**	**Exp. prob. BA by 30**	**Extent of over-optimism**
	Male	1	127	30.71	81.67	50.96
		2	168	55.95	83.88	27.93
		3	226	79.20	91.94	12.74
	Female	1	95	33.68	81.93	48.24
		2	227	55.95	90.04	34.10
		3	361	77.56	94.57	17.00
	Obs	1,204				
Panel B: by parental education and skill	**Parental education**	**Skill**	**Obs**	**Earned BA by age 30**	**Exp. prob. BA by 30**	**Extent of over-optimism**
	Low	1	156	28.85	80.18	51.33
		2	292	51.71	87.66	35.95
		3	350	73.14	92.64	19.50
	High	1	56	42.86	85.57	42.71
		2	80	75.00	89.65	14.65
		3	214	86.45	95.67	9.22
	Obs	1,148				

Notes: Table 16 compares expectations and outcomes across skill quantiles 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.

Table 2 of the main text indicates that those who do not enroll in college have lower expected probabilities of completion compared to enrollees. In our model framework we assume that those who do not enroll in the baseline economy have the same extent of over-optimism as enrollees with the same skill endowment. This abstraction is not relevant for our results on the role of over-optimism in the economy but could be relevant for the experiment where we expand borrowing limits and observe large changes in enrollment choices among those in the lowest skill quantile.

Motivated by this logic, we perform robustness for our estimates of over-optimism in Table 17, which compares the realized graduation rates of those who enroll in each skill quantile with the average expected probabilities of those who never enroll. The implied extent of over-optimism that results can be seen as a lower bound for the over-optimism of the population as a whole, because those who enroll tend to have relatively higher expected probabilities of earning a BA. Comparing Table 17 with Table 1, it is evident that in the NSLY97 over-optimism is present and sizable for the lowest levels of skill regardless of which sample we focus on. In Subsection C.3 of this appendix, we use the beliefs in Table 17 as an alternative target for the calibrated framework and examine how it affects the effects of federal loan limit expansion.

Note that the findings of Table 17 indicate that non-enrollees with high skill exhibit slight pessimism about the probability of earning a BA. This finding speaks to a target population for previous information interventions in studies by Hoxby and Avery (2013), Hoxby and Turner (2015), and Dynarski, Libassi, Michelmore, and Owen (2021), where high-skill students who face challenges (like isolated location or low family income) are targeted with information about the costs and benefits of college, which raises their enrollment likelihood or the quality of the institution they enroll in. For this group of high-skill students who do not enroll in college, we find suggestive evidence for potential benefits of a highly targeted information intervention like those implemented in previous studies. In this paper, however, we are concerned more with aggregate consequences of biases in beliefs—biases which tend to exhibit over-optimism, rather than pessimism, not only on average but especially among those with low skill.

Table 17: Over-optimism among non-enrollees by skill

Skill	**Enr. obs**	**Beliefs obs**	**Earned BA by 30 (enr)**	**Exp. prob. BA by 30**	**Extent of over-optimism**
1	222	585	31.98	64.72	32.74
2	395	417	55.95	69.31	13.36
3	587	161	78.19	72.17	-6.02
Obs	1,204	1,163			

Notes: Table 17 reports over-optimism among high school graduates who did not enroll in a 4-year BA program. Source: NLSY97.

Over-enrollment To estimate the percentage of college students that are over-enrolled in the data, we use the predicted college enrollment as a function of beliefs from model (1) of Table 2 in the main text. Using the coefficients from that estimation, over-enrollment in the data is estimated as the difference between the enrollment rate predicted using reported sample member beliefs and the enrollment rate predicted using realized graduation likelihoods. We then normalize by the percentage enrolled within a skill quantile that is predicted with reported beliefs. The resulting estimated over-enrollment moments from Table 18 are compared with their model counterparts in columns (5) and (6) of Table 10 in the main text.

Table 18: Over-enrollment as a percentage of enrollees by skill quantile

Skill	**Percentage over-enrolled**
1	69.40
2	28.45
3	10.09
Obs	1,204

Notes: Table 18 reports the percentage of college enrollees who would not have enrolled with correct beliefs, by skill quantile. Sample is those who enroll in a 4-year bachelor's degree program by age 30. Source: NLSY97.

Inter vivos transfers In order to estimate average inter vivos transfers from parents to their college-aged children in the NLSY97, we proceed as follows. We use the cleaned data from the earnings process estimation, described in Section A.2 below. Next, we restrict attention to observations where sample members were independents between the ages of 18 and 23 during the years from 1997 to 2003.[55] To account for an implicit transfer from parents to their children who cohabit with them and do not pay rent, we flag those cohabiting with their parents and paying no monthly rent, then impute the average monthly rent paid by sample members with the same family income quantile, college enrollment status, and observation year. 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 ratio reported in the first row of Table 19. The average real values of the components of transfers are also reported. To convert these to real values in 2000 U.S. dollars, we use the Consumer Price Index (CPI).

Table 19: Inter vivos transfers

Variable	**Mean**
Transfer ratio	0.578
Transfers	4,706
Transfers not allowance	539
Allowance	138
Imputed rent	4,671
Obs	8,114
Individuals	2,991

Notes: Table 19 reports average transfers for the sample used to estimate inter vivos transfers. Sample: independents between 18 and 23 observed during 1997-2003. Units for transfer amounts: 2000 $USD. Data are at the individual-year level. Source: NLSY97.

A.2 Earnings process estimation

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_j. The deterministic component depends on the consumer's age, j, their education, e, and their skill en-

[55] We keep observations that are enrolled in post-secondary education, which broadens the sample relative to the earnings estimation in any given year. For independence criteria see National Longitudinal Surveys, https://www.nlsinfo.org/content/cohorts/nlsy97/topical-guide/Income. The NLS criteria for dependency status are not the same as those used in the FAFSA (FSA, 2022b).

dowment (high school GPA), s:

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

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

$$\begin{aligned} \eta_j &= \rho_{\eta,e}\eta_{j-1} + \nu_{e,j} \\ \nu_{e,j} &\sim \mathbb{N}\left(0, \sigma_{\nu,e}\right) \end{aligned}$$

To estimate the earnings process for each education category e, we implement a modification of the approach described in Abbott, Gallipoli, Meghir, and Violante (2019).[56] First, we use the Panel Study of Income Dynamics (PSID) to estimate how logged real wages depend on a third-order polynomial of age for a given education group, $e = \ell$ (HS or some college) or $e = h$ (BA or higher). This identifies $\beta^A_{e,1}$, $\beta^A_{e,2}$, and $\beta^A_{e,3}$ for each education group e. We use the PSID 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 quantiles. The coefficients on skill quantile indicator controls are the factor loadings on skill s for a given education e, $\beta^s_{e,s}$. Finally, using the residuals from the NLSY97 regression, we jointly estimate $\rho_{\eta,e}$ and $\sigma_{\nu,e}$ for each education group. Point estimates are reported in Table 21.

Estimating age profiles in the PSID The PSID collects data on the household head and, if present, their resident spouse (Survey Research Center, Institute for Social Research, 2021). We use information on the educational attainment of the household head and resident spouse (if any), as well as each individual's sex, total income, total income from transfers, total labor earnings, labor component of business income, hours worked, marital status (a flag equal to 1 if married with spouse present, 0 if not) and employment situation (which is used to identify the self-employed). Using this information, we construct unearned income as total income net of earnings and transfers. We construct hourly wages by dividing the individual's labor earnings (plus the labor component of business income when necessary) by total hours worked for the individual.[57] We correct all income and wage variables for inflation using the CPI and thereafter use real dollar values in our

[56] That paper includes gender as a type, while we do not have that kind of heterogeneity. This necessitated re-estimating the earnings profiles so that they are compatible with our model specification.

[57] 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.

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 exclude observations from the SEO census sample and drop observations for whom we do not observe state of residence, marital status, or sex of the household head. We then count the number of times an individual is observed and drop individuals observed fewer than eight times. We compute yearly 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 65 and younger who are greater than 17 if they have a high school degree, greater than 19 if they have some college, and greater than 21 if they have a BA or more. Next, we drop those who are self-employed. We define those with a high school education as individuals who have between 12 and 15 years of education ("high school"); those with a college education are individuals with 16 years or more of education ("BA"). These definitions mean that those with only an associate's degre and dropouts from 4-year bachelor's program are assigned to the high school graduates group in our estimation procedure. The estimation sample has 85,898 individual-year observations for the high school group, and 65,042 for the BA group. Using this estimation sample, we proceed in two stages to account for selection into working within each education category. In the first stage, we regress an indicator for working positive hours on an age polynomial and a set of standard controls (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, X (where Xincludes a constant), in the first stage we also control for Z, which is unearned real income. This first-stage regression can be written as

$$\mathbb{I}_{hrs>0} \quad = \quad \gamma_{e,Z} Z + \alpha_e X + \epsilon$$

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

$$w \quad = \quad \gamma_{e,IM} IM + \beta^A_{e,0} + \beta^A_{e,1} age + \beta^A_{e,2} age^2 + \beta^A_{e,3} age^3 + \gamma_e \times [i.state + i.year + i.married] + u$$

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 $\beta^A_{e,3}$.[58] As

[58]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.

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 by running the same regression augmented with the interaction of a flag for some college, $\mathbb{I}_{\text{SC}}$, with the age polynomial. Results for the interaction terms of this estimation are presented in Table 20; these coefficients are statistically insignificant.

Table 20: Log wages as a function of age: robustness on pooling assumption

Controls	$\log(wage)$
$\mathbb{I}_{\text{SC}} \times$ age	0.0130
	(0.0138)
$\mathbb{I}_{\text{SC}} \times$ age^2	-0.0000750
	(0.000351)
$\mathbb{I}_{\text{SC}} \times$ age^3	-0.000000944
	(0.00000285)
$\mathbb{I}_{\text{SC}}$	-0.167
	(0.174)
R^2	0.119
Obs	85,898

Notes: Table 20 reports regression results. Not shown but included: uninteracted age polynomial, state and year FE, flag for married, inverse Mills ratio, constant. Source: PSID.

Estimating skill loadings in the NLSY97 Our sample keeps only observations where we observe high school GPA, wage, educational attainment, and completion of high school. We correct for inflation using the CPI and drop observations with real wages in dollar units above 400 and below 1 or wage growth above 4 percent or below -2 percent. We drop those with either some high school or with a GED, and those currently enrolled in a BA program, and restrict ages to be above 24 and below 39 so that each age bin has at least 100 observations. We group observations as either "high school" meaning those with a high school degree or some college, or "BA" meaning those with a BA degree or more. Since the NLSY97 records information at the individual level, we reshape the data to be a panel at the individual-year level. We estimate the factor loadings on skill using these remaining observations in the resulting panel data: there are 14,961 observations for the high school group and 8,545 for the BA group.

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 high school GPA quantiles, as well as a set of controls X that include indicators for the year, a set of indicators for the number of children (top-coded at 4), an indicator for being married, and a control for being in the supplemental sample for the NLSY97. Standard errors in this regression are clustered at the individual level. The estimation equation can be written as

$$w_{AF} = \beta^s_{e,0} + \beta^s_{e,s} \times i.\left[GPA_Q = s\right] + \chi X + u$$

where u is the i.i.d. residual.

Estimating the stochastic component of earnings After estimating the skill loadings in the NLSY97, we use the residuals of that regression as inputs to estimate a shock process for each education category. 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.

Summary of earnings process estimation results Table 21 presents the results of the earnings process estimation. We find that earnings increase at a decreasing rate over the life cycle and the college wage premium is lower for those with lower skill endowments. We also find that the stochastic component of the earnings process is more persistent for those with more education, although random-shock variances are similar.

Table 21: Earnings process estimation results

		Value	
Parameter	**Description**	$e = \ell$	$e = h$
$\beta^A_{e,1}$	Age third-order polynomial	0.105	0.182
$\beta^A_{e,2}$		-0.00174	-0.00309
$\beta^A_{e,3}$		0.00000874	0.0000165
$\beta^s_{e,1}$	Skill endowment shifter	-0.0426	-0.180
$\beta^s_{e,2}$		-0.0362	-0.132
$\rho_{\eta\|e}$	Persistence AR(1)	0.855946	0.879158
$\sigma^2_{\nu\|e}$	Variance AR(1)	0.082112	0.078444

Notes: Table 21 summarizes the results from the earnings process estimation. Sources: PSID and NLSY97.

College wage premium by skill quantile Table 22 reports the median wage within each skill quantile by education group. The last column of the table is the college wage premium within each skill quantile, which is the ratio of the two medians. The sample used in Table 22 is at the individual-year level and is the same as what is used at in the earnings process estimation for skill loadings. The wage premia reported in Table 22 are compared with their untargeted model counterparts in Table 27 of Subsection C.1 of this appendix.

Table 22: BA wage premium by skill: ratio of median wages

	High school		Bachelor's degree		
Skill	**Wage**	**Obs**	**Wage**	**Obs**	**Wage premium**
1	10.64	6,902	14.18	880	1.33
2	11.06	5,382	15.56	2,369	1.41
3	11.23	2,677	17.58	5,296	1.57

Notes: Table 22 tabulates the median wage within each high school GPA quantile 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. The last column is the ratio of median wages in the two educational attainment categories. Source: NLSY97.

A.3 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 (U.S. Department of Education, 2020a). We use the public version of the HSLS:09, where this information is reported up to and including the 2015-2016 academic year (Duprey et al., 2020).

The structure of the HSLS:09 is complex.[59] Waves of the study occur in the fall of 2009, in the spring of 2012 (first follow-up), in the summer of 2013 (2013 update), and in the spring of 2016 (second follow-up). High school transcripts are collected during the 2013-2014 academic year, and post-secondary transcripts (as well as student records) are collected in the 2015-2016 academic year (after potentially three full years of academic enrollment in post-secondary education). The second follow-up in the spring of 2016 includes information from students who are currently enrolled in post-secondary education, as well as those who are not enrolled but used to be, and those who did not pursue post-secondary education. If sample members begin a four-year 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 the 2015-2016 academic year. Regardless of persistence status, survey information about the focal sample member includes their high school GPA, as well as any financial aid and private loans they took out to pay for post-secondary education. 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. In all of the tabulations HSLS:09 data moments are weighted using survey weights as noted in the table footnotes.

[59]Questionnaires are available here: National Center for Education Statistics, https://nces.ed.gov/surveys/hsls09/questionnaires.asp.

Expected educational attainment versus outcomes In the first follow-up wave (spring of junior year of high school) the HSLS:09 asks interviewees about their expected educational attainment. Unlike the phrasing of a similar question in the NSLY97, 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. 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 student skill (high school honors-weighted GPA) and educational outcomes (both expected and realized).

Panel A of Table 23 presents, by high school GPA quantile, the percentage of each skill bin that expected to complete a BA program and the percentage of the bin that complete their third academic year of a 4-year BA degree.[60] In particular, Panel A of Table 23 demonstrates 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 quantile.

A concern with the findings reported in Panel A of Table 23 is that responents claim they will get a BA to avoid a stigma 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 quantile still remains well below the expected graduation rate from college, especially for the lowest skill quantile.

Finally, in Panel C of Table 23, we tabulate the parent responses to what they expect their child's

[60]Note that, 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. For this reason, we use terms such as "persistence" and "non-persistence" when discussing findings from the HSLS:09, as opposed to more definitive terms like "dropping out" and "graduating", respectively.

educational attainment will be.[61] Parents tend to overestimate the likelihood of college graduation for their children, especially when their child belongs in a lower skill quantile.

Table 23: Educational attainment outcomes versus expectations

Panel	Sample	Skill	Sample obs	Group obs	% Persisted BA	% Expect BA	Over-optimism
A	Fall 2013 enrollees	1	2,356	155	48	76	29
		2		659	71	80	9
		3		1,542	83	93	10
B	Expect MA+	1	1,356	57	44	100	56
		2		310	70	100	30
		3		989	83	100	17
C	Parent expectations	1	1,021	62	38	76	38
		2		277	71	92	21
		3		682	81	94	13

Notes: Table 23 compares realized and expected bachelor's degree attainment. Samples vary across panels. Weights are PETS-SR student records longitudinal weights. Source: HSLS:09.

Calibration targets and model primitives Table 24 reports moments computed by skill quantile in the HSLS:09 used to discipline our quantitative model. The table includes three categories of moments, indexed with roman numerals: child skill by parental education, tuition and grant aid, and persistence rates. Category I shows that, among students who have graduated from high school, parents with higher education tend to have children in higher skill (high school GPA) quantiles. Category II reports the average tuition paid by each skill quantile of fall 2013 college enrollees. The fact that tuition does not vary greatly across skill quantiles is why the model of the main text includes a pre-subsidy tuition level set to the same value for all college students.[62] The second column in Category II is the ratio of aggregate grants to aggregate tuition and fees within each skill quantile during the first academic year of enrollment. This ratio is used to compute the subsidy rate from public and private grants reported in Table 7 of the main text. Finally, Category III reports moments used to discipline the true probability of completing the third academic year of a BA program, conditional on being enrolled their first year and on being enrolled in their second year in the first and second column, respectively.

Table 25 reports moments describing average labor supply among enrollees and reasons for not enrolling in post-secondary education. The average time spent working per week, for fall 2013 enrollees who persist through their third year, 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, in the

[61] 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.

[62] We relax this assumption in the robustness exercises of Subsection C.3 and find that the results are unchanged.

Table 24: Statistics by skill quantile

		(I) Child skill by parental education		(II) Tuition and grant aid		(III) Percentage persisted (Y3)	
		$\pi\left(s_c \mid e=\ell\right)$	$\pi\left(s_c \mid e=h\right)$	**Tuition + Fees**	$\frac{\textbf{Agg Grants}}{\textbf{Agg Tuition + Fees}}$	**if Enr. Y1**	**if Enr. Y2**
	1	42.64	17.63	17,139	0.407	47.57	77.40
Skill	2	34.08	31.12	17,694	0.462	71.08	86.26
	3	23.28	51.24	19,959	0.520	82.90	91.26

Notes: Table 24 shows statistics by skill quantile for three categories of variables. Category I reports the conditional distribution over high school GPA quantiles among high school graduates given parental education (where $e = h$ denotes at least one parent with BA or more); Category II reports tuition and fees in dollar amounts and total grants as a fraction of tuition and fees during the first academic year for fall 2013 (Y1) enrollees; Category III reports conditional persistence probabilities given enrollment in year 1 (first column) and given enrollment in year 1 and year 2 (second column). Samples vary across categories. Weights are Second Follow-up longitudinal weights for Category I and PETS-SR longitudinal weights for Categories II and III. Source: HSLS:09.

quantitiative model. This evidence uses responses to the question "why did you never enroll in college?" (in this survey question, unlike in the main text and this appendix generally, "college" refers to *any* post-secondary education). Respondents are only asked this question if they say that they never enrolled in post-secondary education, so those who never enroll in a four-year degree program are frequently not asked this question because they may have enrolled in another type of post-secondary program instead. Even conditioning on being asked, non-response rates are high. Nevertheless, when presented with a menu of possible reasons for not enrolling, many respondents indicate that factors such as academics, family, or other reasons that do not include financial or work factors led to them not enrolling in post-secondary education.

Table 25: Labor supply and dependency status, 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	0.244	5,393
	Financial	0.193	
	Work, military, career	0.150	

Notes: Table 25 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 or enrolled in a 4-year degree in the fall of 2013; enrollees are counted as answering 'No' for each possible reason; values are frequencies of answering "Yes' for a given reason. Weights are PETS-SR longitudinal weights for the first row and 2013 Update longitudinal weights for the remaining moments. Source: HSLS:09.

Finally, Table 26, presents regression results for an exercise in which we regress an indicator for persisting to the next academic year on various attributes of the student in the current year. We use an OLS estimator with the dependent variable being indicator for persisting from year 1 to year 2 (model 1 in the table) and from year 2 to year 3 (model 2). The results indicate that high school GPA plays a statistically significant role in predicting persistence early in one's college career, even controlling for several attributes, reinforcing our model specification linking the probability of continuing in college to student skill and year of enrollment.

Table 26: Predicting enrollment persistence in a 4-year BA program

	Persistence	
Controls	**Y2 | Y1**	**Y3 | Y2**
High school GPA	0.09823 (0.02540)	0.06340 (0.02173)
R^2	0.068	0.040
Obs	2,356	2,097

Notes: Table 26 reports results from regressing an indicator for persisting to the next academic year on various controls measured in the current academic year using an OLS estimator. Controls included but not shown in the table: logged household income, logged student debt, logged tuition and fees, hours worked, and flags for having no student debt, not working, having highly educated parents (BA or higher), being female, and a constant. Sample: students who enrolled in a four-year program in the fall of 2013 (Y1); the second column additionally conditions on being enrolled in the 2014-2015 academic year (Y2). Bootstrap standard errors are in parentheses; weights are replicate PETS-SR student records longitudinal weights. Source: HSLS:09.

B Model Appendix

B.1 Value functions

The over-optimistic value of college for $j = 4$ is given by

$$\begin{aligned}
&\hat{V}(j,h,s,\eta,a,x) = \max_{\hat{c}\geq 0,\hat{a}',\hat{x}'} U(c,j,h) - \xi_L \mathbb{I}_{a\geq 0 \text{ and } x=0 \text{ and } (\hat{a}'<0 \text{ or } \hat{x}'>0)} - \xi_L^{pr}\mathbb{I}_{x=0 \text{ and } \hat{x}'>0} \qquad (14)\\
&+ \beta\psi_j[\hat{p}(s)E_{\eta'|h,\eta}V(j+1,h,s,\eta',\hat{a}',\hat{x}') + (1-\hat{p}(s))E_{\eta'|\ell,\eta}V(j+1,\ell,s,\eta',\hat{a}',\hat{x}')]\\
&s.t.\\
&(1+\tau_c)\hat{c} + \hat{a}' + (1-\theta(s)-\theta^{pr}(s))\kappa = y_{j,h,s,\eta,a} + a + Tr_j - T(y_{j,h,s,\eta,a}) + (\hat{x}'-x)\\
&\hat{a}' \geq -\bar{A}\left(\tfrac{j}{4}\right)[(1-\theta(s)-\theta^{pr}(s))\kappa + \bar{c}]\\
&\hat{a}' \leq a \text{ if } a \leq 0\\
&\hat{x}' - x \in \left[0, [(1-\theta(s)-\theta^{pr}(s))\kappa + \bar{c}] - [\max(-\hat{a}',0) - \max(-a,0)]\right]
\end{aligned}$$

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, x). The consumer's value function is given by

$$V(j,e,s,\eta,a,x) = \max_{d_f,d_x}(1-d_f)(1-d_x)V^R(j,e,s,\eta,a,x)+ \tag{15}$$
$$d_f(1-d_x)V^{D_f}(j,e,s,\eta,a,x) + (1-d_f)d_xV^{D_x}(j,e,s,\eta,a,x) + d_fd_xV^D(j,e,s,\eta,a,x)$$

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

$$V^R(j,e,s,\eta,a,x) = \max_{c\geq 0,a'} U(c,j,e) + \beta\psi_j E_{\eta'|e,\eta}V(j+1,e,s,\eta',a',x') \tag{16}$$
$$s.t.$$
$$(1+\tau_c)c + a' = y_{j,e,s,\eta,a} + a + \mathbb{I}_{\{a<0\}}r_{SL}a + Tr_j - T(y_{j,e,s,\eta,a}) - \rho_R^{pr}(j,x)$$
$$a' \begin{cases} = (1+r_{SL})a + \rho_R(j,a) & \text{if } a < 0 \\ \geq 0 & \text{if } a \geq 0 \text{ and } x = 0 \\ = 0 & \text{otherwise } (a \geq 0 \text{ and } x > 0) \end{cases}$$
$$x' = x(1+r_{SL}^{pr}) - \rho_R^{pr}(j,x)$$

Alternatively, these consumers can choose delinquency on either type of loan or on both loans. If a consumer chooses delinquency on only federal loans, their value function for $j > 4$ and $j \neq j_f + j_a$ is given by

$$V^{D_f}(j,e,s,\eta,a,x) = U(c,j,e) - \xi_D + \beta\psi_j E_{\eta'|e,\eta}V(j+1,e,s,\eta',a',x') \tag{17}$$
$$s.t.$$
$$(1+\tau_c)c = y_{j,e,s,\eta,a} + Tr_j - T(y_{j,e,s,\eta,a}) - \rho_D(j,a,y_{j,e,s,\eta,a}) - \rho_R^{pr}(j,x)$$
$$a' = (1+r_{SL})a + \rho_D(j,a,y_{j,e,s,\eta,a}) - \phi_D[\rho_R(j,a) - \rho_D(j,a,y_{j,e,s,\eta,a})]$$
$$x' = x(1+r_{SL}^{pr}) - \rho_R^{pr}(j,,x)$$

where ξ_D is the stigma cost of choosing delinquency on federal loans. In the case of non-repayment of federal loans, 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 federal loans and full payment on private loans. As mentioned in Section 3.3, ϕ_D is the fraction of missed payment (difference between full payment and partial payment) that is charged as a collection fee. The outstanding principal plus interest is then augmented by the missed payment plus the collection fee (net of any partial payment). Similarly, if a consumer chooses delinquency on only private loans, their value function for $j > 4$ and $j \neq j_f + j_a$ is given by

$$V^{D_x}(j,e,s,\eta,a,x) = U(c,j,e) - \xi_D^{pr} + \beta\psi_j E_{\eta'|e,\eta} V(j+1,e,s,\eta',a',x') \tag{18}$$
$$s.t.$$
$$(1+\tau_c)c + a' = y_{j,e,s,\eta,a} + a + \mathbb{I}_{\{a<0\}} r_{SL} a + Tr_j - T(y_{j,e,s,\eta,a}) - \rho_D^{pr}(j,x,y_{j,e,s,\eta,a})$$
$$a' = \mathbb{I}_{a<0}(1+r_{SL})a + \rho_R(j,a)$$
$$x' = (1+r_{SL}^{pr})x - \rho_D^{pr}(j,x,y_{j,e,s,\eta,a}) + \phi_D[\rho_R^{pr}(j,x) - \rho_D^{pr}(j,x,y_{j,e,s,\eta,a})]$$

where ξ_D^{pr} is the stigma cost of choosing delinquency on private loans. As in the case of delinquency on only federal loans, here the consumer does not make a consumption-savings decision. Instead, they pay the fixed amount of federal student loans repayment $\rho_R(j,a)$, and are subject to wage garnishment because of delinquency on private loans. The garnishment amount is denoted by $\rho_D^{pr}(j,x,y_{j,e,s,\eta,a})$, as described in Section 3.3. Similar to the case of delinquency on federal loans, the consumer faces a collection fee, which is equal to a fraction ϕ_D multiplied by the difference between full payment and partial payment on private loans.

Lastly, the value of choosing delinquency on both types of loans is given by

$$V^{D}(j,e,s,\eta,a,x) = U(c,j,e) - \xi_D - \xi_D^{pr} + \beta\psi_j E_{\eta'|e,\eta} V(j+1,e,s,\eta',a',x') \tag{19}$$
$$s.t.$$
$$(1+\tau_c)c = y_{j,e,s,\eta,a} + Tr_j - T(y_{j,e,s,\eta,a}) - \rho_D(j,a,y_{j,e,s,\eta,a}) - \rho_D^{pr}(j,x,y_{j,e,s,\eta,a})$$
$$a' = (1+r_{SL})a + \rho_D(j,a,y_{j,e,s,\eta,a}) - \phi_D[\rho_R(j,a) - \rho_D(j,a,y_{j,e,s,\eta,a})]$$
$$x' = (1+r_{SL}^{pr})x - \rho_D^{pr}(j,x,y_{j,e,s,\eta,a}) + \phi_D[\rho_R^{pr}(j,x) - \rho_D^{pr}(j,e,x,y_{j,e,s,\eta,a})]$$

A consumer who chooses this outcome is subject to stigma cost, wage garnishment, and a collection fee (analogous to the previous two cases) from both the federal student loan program and the private lender; their consumption for the current period and outstanding loan balances for the next period follow from the same set of delinquency rules described above. When $j = j_f + j_a$ and the consumer chooses delinquency, we assume those consumers cannot make a familial inter vivos transfer in order to be consistent with our assumption that consumers cannot save until they have paid off their student loans. Therefore, the value functions for delinquency are largely the same as in equations (17)-(19), with the difference that the parent has a term reflecting altruistic utility toward their child, represented by the addition of $\beta_c E_{\eta'|l} \hat{W}(s_c,\eta',b=0)$ to the objective function.

B.2 Equilibrium definition

To define the equilibrium, we must first discuss notation, define the Social Security transfer function, and present the zero expected profit condition that pins down the private student loan interest rate. Let $\overrightarrow{\omega}$ denote the idiosyncratic state of a consumer. This state depends on age and enrollment status in the following way:

$$\overrightarrow{\omega} = \begin{cases} (s, \eta, a) & \text{for 18-year-olds, before making the college entrance decision} \\ (j, h, s, \eta, a, x) & \text{for consumers in college} \\ (j, e, s, \eta, a, x) & \text{for consumers not enrolled, dropouts, or graduates, if } j \neq j_f + j_a \\ (j, e, s, \eta, a, x, s_c) & \text{if } j = j_f + j_a \end{cases} \tag{20}$$

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

Private loan interest rate: $r^{pr}_{SL,t}$ is such that the lender makes zero expected profits in pooling each cohort of 18-year-old-consumers. The zero expected profit condition is given by

$$\begin{aligned} &\sum_{i=1}^{4}(\beta)^{i-1}\int((1+\tau_{is})x'_{t+i-1}(\overrightarrow{\omega})-x)\Omega_{t+i-1}d(\overrightarrow{\omega}|j=i) = \\ &\sum_{i=5}^{J}(\beta)^{i-1}\int\Bigg[(1-d_{x,t+i-1}(\overrightarrow{\omega}))\rho^{pr}_{R}(j,x)+ \\ &d_{x,t+i-1}(\overrightarrow{\omega})\big[\rho^{pr}_{D}(j,x,y_{j,e,s,\eta,a})-\phi_D[\rho^{pr}_{R}(j,x)-\rho^{pr}_{D}(j,x,y_{j,e,s,\eta,a})]\big]\Bigg]\Omega_{t+i-1}d(\overrightarrow{\omega}|j=i), \end{aligned} \tag{21}$$

where β is the lender's discount factor and τ_{is} is a student loan issuance cost.

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

$$ss_{e,s} = \frac{\chi}{2}\left[\frac{\int w\eta\epsilon_{j,e,s}\Omega_t d(\overrightarrow{\omega}|18 \leq j < j_r, e, s)}{\int \Omega_t d(\overrightarrow{\omega}|18 \leq j < j_r, e, s)} + \frac{\int w\eta\epsilon_{j,e,s}\Omega_t d(\overrightarrow{\omega}|18 \leq j < j_r)}{\int \Omega_t d(\overrightarrow{\omega}|18 \leq j < j_r)}\right] \tag{22}$$

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 $\{\hat{W}_t(\overrightarrow{\omega}), V_t(\overrightarrow{\omega}), \hat{V}_t(\overrightarrow{\omega}), V^R_t(\overrightarrow{\omega}), V^D_t(\overrightarrow{\omega}), V^{D_f}_t(\overrightarrow{\omega}), V^{D_x}_t(\overrightarrow{\omega})\}$, 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 $\{d_{f,t}(\overrightarrow{\omega}), d_{x,t}(\overrightarrow{\omega})\}$, household inter vivos transfer policy function $\{b_t(\overrightarrow{\omega})\}$, production plans $\{Y_t, K_t, L_t\}$, tax policies $\{\gamma_t\}$, prices $\{r_t, w_t, r^{pr}_{SL,t}\}$, Social Security transfers $\{ss_{t,e,s}\}$, accidental bequests $\{Tr_{t,j}\}$, and measures $\{\Omega_t(\overrightarrow{\omega})\}$ such that:

(i) Given prices, transfers, and policies, the value functions and household policy functions solve the consumer problems in equations (1)-(6) and (14)-(19);
(ii) The saving interest rate and wage rate satisfy equations firm first order conditions;
(iii) The private student loan interest rate satisfies equation (21);
(iv) Social Security transfers satisfy equation (22);
(v) Accidental bequests are transferred to households between ages 50 and 60 $(33 \leq j \leq 43)$ after deducting expenditure on private education subsidies[63]

$$Tr_{t+1,j} = \frac{\int (1-\psi_j) a'_t(\overrightarrow{\omega})\Omega_t d(\overrightarrow{\omega}) - \kappa \int \theta^{pr}(s)\mathbb{I}_{e=h \text{ and } j\in\{1,2,3,4\}}\Omega_{t+1} d(\overrightarrow{\omega})}{\sum_{j=33}^{43} N_{t+1,j}} \tag{23}$$

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

$$\int [\tau_c c_t(\overrightarrow{\omega}) + T(y_{t,j,e,s,\eta,a})]\Omega_t d(\overrightarrow{\omega}) = G_t + E_t + D_t + SS_t \tag{24}$$

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;
(vii) Labor, capital, and goods markets clear in every period t; and
(viii) $\Omega_{t+1} = \Pi_t\Big(\Omega_t\Big)$, 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, and college continuation probabilities.

B.3 Computational algorithm for the stationary equilibrium

1. Guess interest rate r_{guess}, wage rate w_{guess}, private student loan interest rate $r^{pr}_{SL,\text{guess}}$), 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 (15)-(19))

[63] 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 overly optimistic value function before college, $\hat{W}_{\text{guess}}(s, \eta, a)$ (equation (1))

4. Use backward induction to solve consumer problem: $j = 1, \ldots, j_f + j_a$ (equations (1)-(6) and (14))
   - In solving consumer problem at $j = j_f + j_a$, use $\hat{W}_{\text{guess}}(s, \eta, a)$ for altruistic term
   - For consumers before college graduation age, not in college, and without loans, ($j \leq 4, e = \ell, a \geq 0, x = 0$), and for consumers after college graduation age and without loans, ($j > 4, a \geq 0, x = 0$), 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 $a < 0$ or $x > 0$) and, for consumers after college graduation age with loans ($j > 4, a < 0$ or $x > 0$), use discrete grid search for optimization as these consumers may choose delinquency

5. Use new value before college to update $\hat{W}_{\text{guess}}(s, \eta, a)$; repeat 4.-5. until convergence

6. Guess initial distribution of 18-year-old consumers $\Omega(j = 1, s, \eta, a)_{\text{guess}}$

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 $\Omega(j = 1, s, \eta, a)$

9. Update $\Omega(j = 1, s, \eta, a)_{\text{guess}}$ 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 rate the firm's first order conditions
    - Compute private loan interest rate using zero-expected-profit condition (equation (21))
    - Compute γ using the government budget constraint (equation (24))
    - Compute accidental bequests and Social Security transfers (equations (23) and (22))

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 over-optimism about likelihood of college continuation 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

$$\tilde{V}(j,e,s,\eta,a,x) = \sum_{s_c} \pi(s_c|e)[(1-d_f)(1-d_x)\tilde{V}^R(j,e,s,\eta,a,x,s_c)+ \tag{25}$$
$$d_f(1-d_x)\tilde{V}^{D_f}(j,e,s,\eta,a,x,s_c) + (1-d_f)d_x\tilde{V}^{D_x}(j,e,s,\eta,a,x,s_c) + d_f d_x \tilde{V}^D(j,e,s,\eta,a,x,s_c)]$$

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

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

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

$$\tilde{V}(j,h,s,\eta,a,x) = U(c,j,h) - \xi_L \mathbb{I}_{a\geq 0 \text{ and } x=0 \text{ and } (a'<0 \text{ or } x'>0)} - \xi_L^{pr}\mathbb{I}_{x=0 \text{ and } x'>0} \tag{26}$$
$$+ \beta\psi_j[p_c(j,s)E_{\eta'|h,\eta}\tilde{V}(j+1,h,s,\eta',a',x') + (1-p_c(j,s))E_{\eta'|\ell,\eta}\tilde{V}(j+1,\ell,s,\eta',a',x')]$$

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

$$\begin{aligned}\tilde{W}(s,\eta,a) =& q[(1-\hat{d}_e)\tilde{V}(1,\ell,s,\eta,a,x=0) + \hat{d}_e\tilde{V}(1,h,s,\eta,a,x=0)] \\ &+ (1-q)\tilde{V}(1,\ell,s,\eta,a,x=0)\end{aligned} \tag{27}$$

where the planner takes as given the enrollment decision $\hat{d}_e(\cdot)$, which solves equation (1). This value function is the second of the two instances in which the planner's computation differs from that of the overly-optimistic consumer. The planner uses $\tilde{V}(\cdot)$, which uses the true probability $p_c(j,s)$ for likelihood of continuation, whereas the over-optimistic consumer uses $\hat{V}(\cdot)$, which uses the over-optimistic probability $\hat{p}(s)$ for likelihood of college continuation.

To measure welfare for the 18-year-old consumer, we use the 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/psychic costs. For the average 18-year-old in period t, consumption equivalent variation, $g_{c,t}$, is computed using the following equation

$$(1+g_{c,t})^{1-\sigma}\int \mathbb{I}_{\{j=1\}}\tilde{V}_{\text{initial}}(1,\ell,s,\eta,a,x=0)\Omega_{\text{initial}}d(\overrightarrow{\omega}) = \int \mathbb{I}_{\{j=1\}}\tilde{W}_t(s,\eta,a)\Omega_t d(\overrightarrow{\omega}) \quad (28)$$

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, we report the difference in lifetime consumption units between period t and the initial stationary equilibrium (i.e., $100\times(g_{c,t}-g_{c,\text{initial}})$). 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 (28).

C Results Appendix

C.1 Baseline initial steady state: additional properties

Table 27 reports the college wage premium by skill in the data and the baseline model. Data moments are from the NLSY97, as reported in Table 22 of Appendix A.2. 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). The model does remarkably well in explaining these untargeted college wage premiums.

Table 27: College wage premium by skill quantile

Skill	Data	Model
1	1.33	1.31
2	1.41	1.44
3	1.57	1.59

Notes: Table 27 reports the college wage premium in the NLSY97 and in the baseline model.

Table 28 reports loan uptake by persistence status for a given cohort of enrollees in the data (Panel A, from Table 3 in Section 2.2) and in the model baseline (Panel B). Although these moments are untargeted in our calibration, the model does reasonably well in accounting for aggregate balance shares in column (2) and the magnitude of loan balances among student debtors in columns (4) and (5). However, the model does not perform well in capturing the share of non-persisters with any student debt in column (3). We attribute this to fewer dropouts having small loan balances in the model as compared to the data.

Table 28: Student loans by persistence status: data versus model baseline equilibrium

Panel	Source	Persistence status	(1) % of enrollees	(2) % of SL $	(3) % with SL	(4) Average $	(5) Median $
A	Data	Did not persist	24	19	78	15,270	12,238
		Persisted	76	81	65	24,648	19,500
B	Model	Did not persist	27	8	14	21,898	16,755
		Persisted	73	92	56	25,478	12,100

Notes: Table 28 reports loan uptake patterns by persistence status to the third academic year for a given cohort of enrollees. Panel A contains moments from the HSLS:09, as reported in Table 3. Panel B contains analogous statistics from the model baseline equilibrium.

The loan statistics in Table 28 condition on college enrollment. Holding everything else fixed, over-optimism mostly affects the enrollment decision rather than loan uptake conditional on enrollment. Therefore, the statistics reported in Table 28 will barely change if we computed the same statistics without over-optimism. Of course, total borrowing will be affected by over-optimism because total student debt depends on how many young adults choose to enroll in college. To see this, one can consider a partial equilibrium where beliefs are corrected for high school graduates, after family transfers are made but before the enrollment decision. With correct beliefs, college enrollment falls, so that while dropouts have similar loan uptake behavior once enrolled, the mass of this group is now smaller. The aggregate debt owed by dropouts in the partial equilibrium with correct beliefs decreases accordingly. Specifically, just before student loan repayment begins, for a given cohort of high school graduates, the mass of student debtors who are dropouts falls by 9 percent, while the aggregate balances held by dropouts also fall by 9 percent. These changes are sizable, yet debt held by dropouts remains large even with correct beliefs. This illustrates that student debt held by dropouts, as observed in the model's baseline equilibrium, is mostly a consequence of the intrinsic riskiness of college as an investment.

In Table 29, we analyze how family inter vivos transfers change in partial equilibrium when over-optimism is eliminated for all consumers. Panel A of Table 29 reports in column (1), the transfers parents make on average given the child's skill bin, whereas column (2) reports the transfers the same distribution of parents would make in the same baseline equilibrium if there were no over-optimism. Transfers in Panel A are reported as a percent of GDP per capita for the population that is 18 and over in the baseline equilibrium. Column (3) reports the difference between columns (1) and (2). If over-optimism is eliminated, parents with low- and medium-skill children will

Table 29: Family transfer statistics by skill quantile

Panel A: Family transfers with and without over-optimism	**Skill**	**Average family transfer (1) Baseline**	**(2) No over-optimism**	**Change in transfers (3) = (2) - (1)**
Units: percent of baseline p.c. GDP for 18+	1	44.23	31.43	-12.79
	2	61.45	51.40	-10.05
	3	69.14	73.20	4.07
Panel B: Distribution of changes in family transfers	**Skill**	**Changes in transfers after correcting beliefs (1) Increase**	**(2) No change**	**(3) Decrease**
Units: percent of cohort	1	7.16	68.43	24.41
	2	2.33	71.03	26.64
	3	21.50	77.41	1.09

Note: Table 29 presents family transfer statistics by skill quantile in the baseline model equilibrium. In Panel A, columns (1) and (2) report the transfers parents would make in the baseline case and in the case without over-optimism; column (3) reports the difference between the no over-optimism and the baseline transfer levels. In Panel B, columns (1) to (3) report the share of children that experience an increase, no change, or decrease in transfers if over-optimism is eliminated.

transfer lower amounts while parents with high-skill children will transfer higher amounts. To see what is driving these changes, Panel B reports the share of 18-year-olds in a given skill bin that would experience an increase, no change, or a decrease in transfers if over-optimism is eliminated. Conditional on parents changing their transfers, transfers decrease for most 18-year-olds with low and medium skill, whereas transfers increase for most 18-year-olds with high skill.

The reason for the changes in Panel B of Table 29 being negative for low- and medium-skill and positive for high-skill children is that transfers play different roles for those groups. Generally, transfers act as a source of funds for human capital investment and as a source of financing for consumption. For low- and medium-skill children, the transfer from their parents increase their incentive to attend college by alleviating credit frictions. Therefore, from the parent's perspective, the transfer acts to affect the enrollment decision and so predominantly plays the role of an investment in the child's education. Over-optimism inflates the expected return to the child's education, so that eliminating over-optimism makes incentivizing enrollment look less appealing for parents. Their transfers drop accordingly. By contrast, a high-skill child has a large incentive to go to college regardless of the transfer they receive from their parent. Family transfers for these children predominantly act to increase consumption directly, rather than indirectly by boosting human capital investment. When the parent realizes that their high-skill child is less likely to graduate (after beliefs are corrected), they respond by using transfers to directly raise their child's future consumption regardless of the graduation outcome.

C.2 Elimination of over-optimism: enrollment and tax analysis

In Panel A of Table 30, columns (1) and (2) report changes in over-enrollment and college enrollment rates by skill from the initial to the final steady state when over-optimism is eliminated in the baseline model. As the two columns indicate, the fall in college enrollment is larger than the fall in over-enrollment. This subsection discusses why that happens and its implication for the income tax rate. To provide economic intuition, we analyze the elimination of over-optimism in the following two cases: in column (3), prices, the income tax rate parameter, bequests, and Social Security transfers are fixed at their initial steady state values, but the 18-year-old distribution is allowed to change; in column (4), the 18-year-old distribution is fixed at its initial steady state level, but prices, the income tax rate parameter, bequests, and Social Security transfers are allowed to adjust to satisfy their respective equations. In column (3), college enrollment rates fall as much as they do in the baseline. This suggests that enrollment rate changes are driven mainly by either 18-year-olds correcting their beliefs or because their distribution over initial assets or skill changes. Column (4) in Panel A shows that when the 18-year-old distribution is fixed, but other general equilibrium objects are allowed to adjust, the drop in college enrollment rates match the drop in over-enrollment in the baseline. We conclude that changes in the 18-year-old distribution contribute to the larger fall in college enrollment compared to over-enrollment.

When over-optimism is eliminated, the 18-year-old distribution changes because parents reduce transfers. This is because they update their beliefs, the economy becomes poorer, and children become lower skilled. Panel B reports statistics analogous to that of Panel A, but from the initial steady state to the first transition period rather than the final steady state. The changes in Panel B are nearly the same as those in Panel A. Therefore, parents reducing transfers due to adjustments in beliefs must drive the lower college enrollment because the other distributional reasons would not have kicked in the first period of the transition. Panel B establishes that the primary driver of the fall in college enrollment (beyond the fall in over-enrollment) is parents reducing their transfers after beliefs are corrected.

In Panel C, we show that the mechanism highlighted above also matters for the increase in the income tax rate. In the baseline general-equilibrium model, the fall in college enrollment leads to an increase in the income tax rate of 0.57 percentage points for an individual with the initial steady state mean income. College enrollment falls because 18-year-olds no longer over-enroll and also because parents update their beliefs and reduce transfers. The effect of the latter on the income tax rate is significant. In column (4), when we consider the case where the 18-year-old distribution is fixed, but other general equilibrium objects are allowed to adjust, we see that the income tax rate increases by 0.20 percentage points. This suggests that adjustments in the 18-year-old distribution explains the remainder of the increase in the income tax rate of 0.37 percentage points.

Table 30: Elimination of over-optimism: changes from initial steady state ...

Panel A: ... to final steady state	Over-enrollment	College enrollment rate		
Skill	**(1) Baseline**	**(2) Baseline**	**(3) Endogenous Ω_{18}**	**(4) Exogenous Ω_{18}**
1	-15.77	-20.25	-20.21	-15.77
2	-5.57	-23.58	-23.49	-5.57
3	0.00	0.00	0.00	0.00
Panel B: ... to first transition period	**Over-enrollment**	**College enrollment rate**		
Skill	**(1) Baseline**	**(2) Baseline**	**(3) Endogenous Ω_{18}**	**(4) Exogenous Ω_{18}**
1	-15.77	-19.13	-19.22	-15.77
2	-5.57	-20.53	-20.55	-5.57
3	0.00	0.00	0.00	0.00
Panel C: ... to final steady state		**Income tax rate | Initial steady state mean income**		
		(2) Baseline	**(3) Endogenous Ω_{18}**	**(4) Exogenous Ω_{18}**
		0.57	0.00	0.20

Notes: Panels A and B report changes in enrollment statistics by skill resulting from an elimination of over-optimism from the initial steady to the final steady state and the first period of the transition, respectively. Columns (1) and (2) report changes in over-enrollment and college enrollment rates from the baseline model. Column (3), "Endogenous Ω_{18}", reports changes in the college enrollment rates when prices, the income tax rate, bequests, and Social Security transfers are fixed at their initial steady state values, but the 18-year-old distribution is allowed to change. Column (4), "Exogenous Ω_{18}", reports changes in the college enrollment rates when the 18-year-old distribution is fixed at its initial steady state level, but prices, the income tax rate, bequests, and Social Security transfers are allowed to adjust to satisfy their respective equations. Panel C reports changes in the income tax rate given the initial steady mean income from the initial steady state to the final steady under each model variation. All units are in percentage points.

C.3 Main experiments: sensitivity analyses

In this section, we perform several sensitivity analyses by considering alternative variations of the baseline model. In each case, the model variation is re-calibrated to target the same set of moments as the baseline calibration to the extent possible. The welfare implications under each variation for the two main experiments are shown in Figures 5 and 6.

No learning about over-optimism In this sensitivity analysis, we consider the case in which students never learn their true continuation probabilities and continue to be over-optimistic for the whole duration of college. A comparison of Subfigure 5a to Subfigure 5b and Subfigure 6a to Subfigure 6b shows that the welfare implications of the two main experiments barely change. The assumption about learning does not matter because most drop outs happen between the first and second year of college.

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. Subfigures 5c and 6c show that the welfare implications barely change in this case as well. The lack of impact from a higher add-on to the federal interest rate suggests that students are interest inelastic to small perturbations in the parameter space for the cost of borrowing implied by the baseline model.

Non-enrollees' beliefs as targets In this sensitivity analysis, we consider an extremely conservative calibration where we target the expected likelihood of BA attainment of those who do not enroll in college by age 30, as reported in Panel A of Table 17 in Subsection A.1. This is an extremely conservative calibration because in our model, within a skill bin, all 18-year-olds have the same beliefs about the likelihood of college graduation. Subfigures 5d and 6d show the welfare implications from the two main experiments. Even with this extremely conservative calibration (although magnitudes are smaller) the elimination of over-optimism leads to welfare losses and an expansion in the federal student loan limits hurts low skill 18-year-olds.

Flat income taxation In our baseline model, income taxation is progressive. In the presence of flat income taxation (with government consumption still set as a constant fraction of output), a college education does not have a fiscal externality because high income college graduates do not pay a higher marginal tax rate. To demonstrate this, in this sensitivity analysis we analyze a variation with flat income taxation ($\tau_p = 0$). Subfigure 5e shows that the costs of eliminating over-optimism are dampened compared to the baseline. In fact, some 18-year-olds in the early periods of the transition experience significant gains while the low skill 18-year-olds experience gains in all periods. Welfare takeaways from a federal loan limit expansion do not change (Subfigure 6e).

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.[64] 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 24 as target moments. Subfigures 5f and 6f show that the key welfare insights from the two main experiments do not change.

Lower private loan uptake cost In the baseline model, we calibrated the private loan uptake cost, ξ_L^{pr}, to target the total loan uptake of private students loans. This cost generates a pecking order in the model consistent with the data, where students borrow from the federal student loan program before turning to private lenders. The first two rows of Table 31 compare the student loan portfolio composition between data and the baseline model. While the baseline model does remarkably well in explaining the student portfolio composition observed in the data, one could argue that in the data, the uptake of "Only private" loans is 2 percent, whereas that statistic in the baseline model is 0. In this sensitivity analysis, we calibrate the private loan uptake cost to target

[64] The higher benefits of college for higher skill students is captured through the higher college wage premium in our model.

the "Only private" loan uptake of 2 percent instead of the "Any private" loan uptake of 22 percent. In this calibration, ξ_L^{pr} is equal to 0.570, as opposed to 2.713 in the baseline calibration, so the cost is almost 80 percent lower.[65] As Subfigure 5g shows, although the magnitudes are different, the elimination of over-optimism leads to welfare losses in the long run. Subfigure 6g shows that a federal student loan limit expansion leads to gains for the high skill and losses for the low skill, although the magnitudes are smaller. This is because, with a lower ξ_L^{pr}, the substitutability between federal and private students loans is higher. Although this calibration accounts for uptake of "Only private" loans, as Table 31 shows, it significantly understates the uptake of "Only federal" student loans and overstates the uptake of "Any private" student loans. Therefore, the baseline calibration is our preferred calibration.

Table 31: Student loan portfolio composition in data and model

Case	Either	Only federal	Only private	Both	Any private
Data	65	44	2	20	22
Model: baseline	56	34	0	22	22
Model: lower private loan uptake cost	58	10	2	46	48

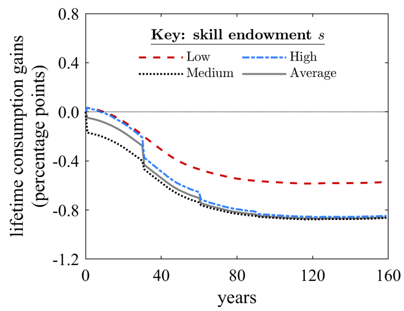
Notes: Table 31 reports the share of students who owe money for either, only federal, only private, both types, or any private student loans three years after enrollment in the data, the baseline model, and a variation of the model that is re-calibrated with a lower private loan uptake cost. Numbers in italics in the model rows are calibration targets to discipline the loan uptake costs. Percentages are rounded to the nearest percentage point, so the sum of the last three columns may not exactly equal the value in the first column. Weights are PETS-SR student records longitudinal weights. Source: HSLS:09.

College enrollment option shock that depends on skill In our baseline calibration, the college enrollment option shock, q, does not depend on skill. In this sensitivity analysis, we consider the case where the q shock depends on skill. We calibrate the shock by targeting enrollment rates for high school graduates in the highest family income quantile for each skill bin instead of the overall enrollment rate for the highest skill quantile. The empirical estimates for enrollment rates by skill quantile in the highest family income quantile are given in Table 14. As shown in Subfigures 5h and 6h, the key welfare insights from the two main experiments do not change.

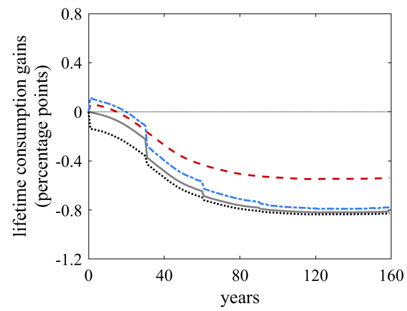
Skill does not depend on parental education In our baseline calibration, the child's skill depends on parental education. Our calibrated estimates imply that high education parents are more likely to have children with higher skill (see Table 24). In this sensitivity analysis, we relax this assumption and consider the case where the child's skill does not depend on parental education. We do this by

[65] A lower cost for ξ_L^{pr} generates a positive "Any private" loan uptake for the following reason. In our baseline model framework, the only benefit of private student loans over federal student loans is that college enrollees can save when they borrow from private lenders, but cannot save when they borrow from the federal student loan program. This captures a mechanism similar to the Expected Family Contribution (EFC), where students from richer families face lower federal student loan limits due to higher EFCs, and so turn to private lenders for borrowing.

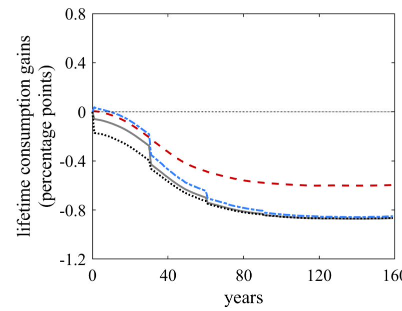
setting $\pi(s_c|e) = 1/3$ for all s_c and e. Subfigures 5i and 6i show that the key takeaways from the main experiments do not change.



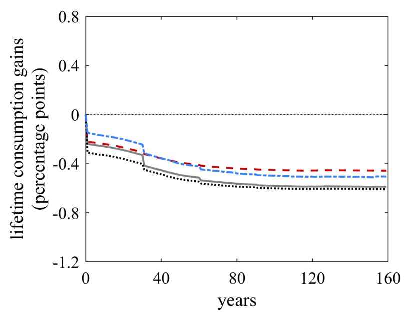
(a) Baseline



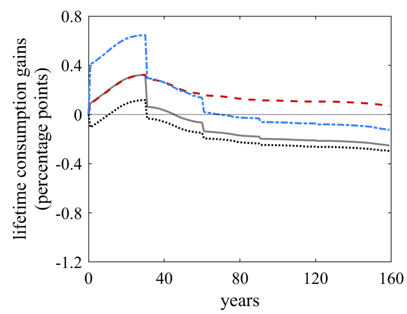
(b) No learning about over-optimism



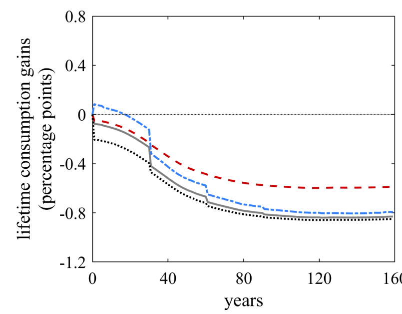
(c) Higher add-on for federal SL



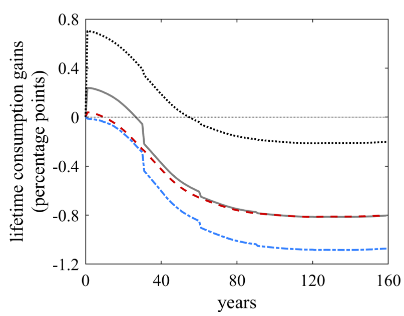
(d) Non-enrollees' beliefs as targets



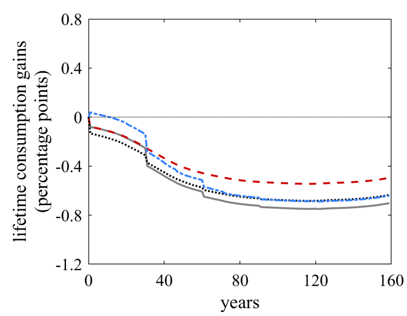
(e) Flat income taxation



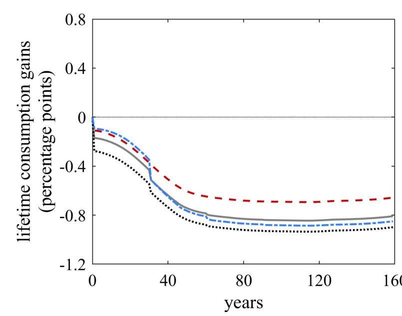
(f) Tuition | Skill



(g) Lower private loan uptake cost



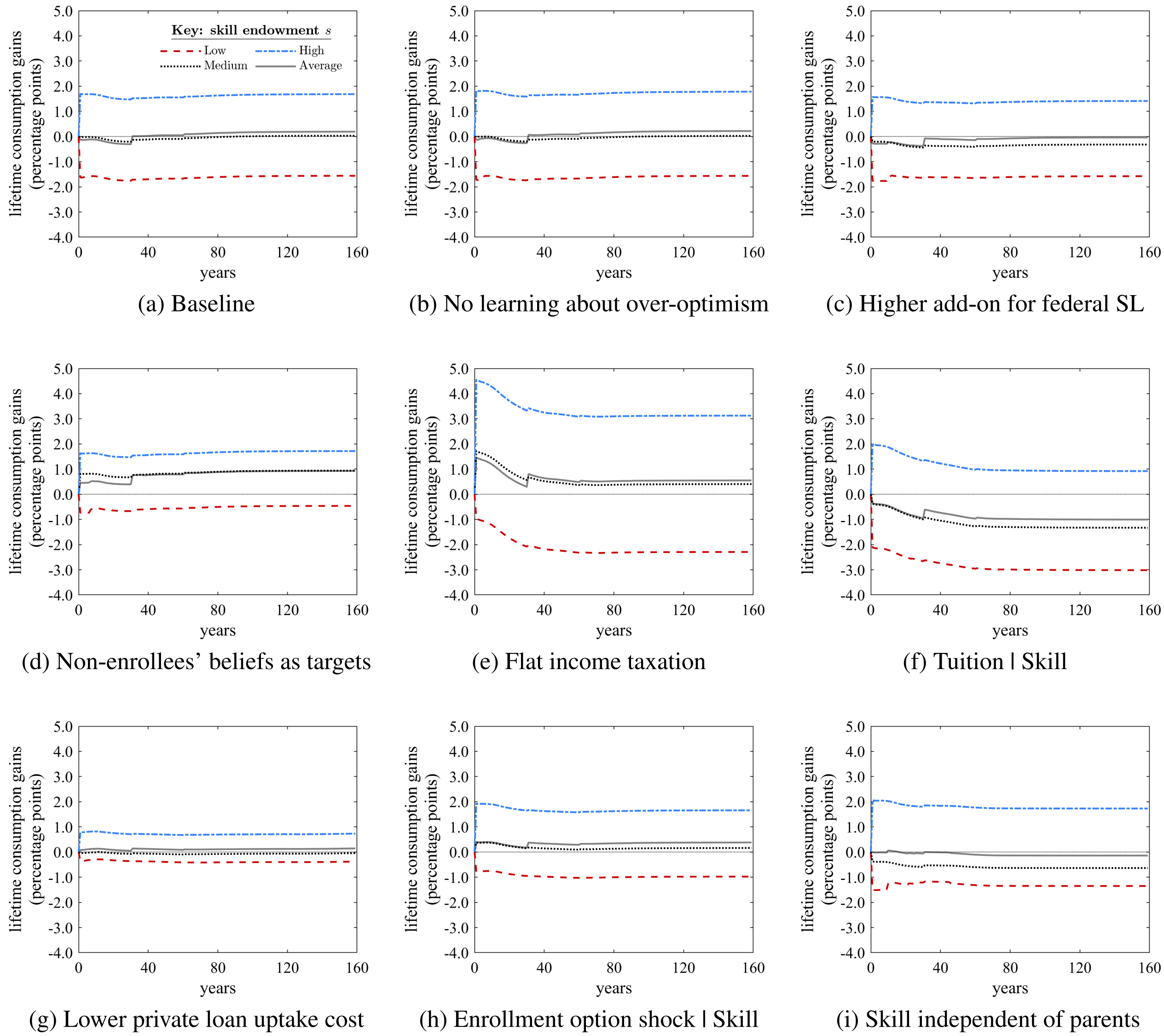
(h) Enrollment option shock | Skill



(i) Skill independent of parents

Figure 5: Sensitivity analyses for elimination of over-optimism: welfare

Notes: Figure 5 plots welfare implications of eliminating over-optimism under the following cases: (a) baseline, (b) students do not learn about over-optimism for the whole duration of college, (c) higher add-on for the federal student loan interest rate, (d) non-enrollees' expected likelihood of BA attainment used as beliefs targets, (e) flat income taxation, (f) college tuition depends on skill, (g) lower uptake cost for private loans, (h) college enrollment option shock depends on skill, and (i) skill does not depend on parental education. Each variation of the baseline model is re-calibrated.



(a) Baseline (b) No learning about over-optimism (c) Higher add-on for federal SL

(d) Non-enrollees' beliefs as targets (e) Flat income taxation (f) Tuition | Skill

(g) Lower private loan uptake cost (h) Enrollment option shock | Skill (i) Skill independent of parents

Figure 6: Sensitivity analyses for federal loan limit expansion: welfare

Notes: Figure 6 plots welfare implications of a federal student loan limit expansion under the following cases: (a) baseline, (b) students do not learn about over-optimism for the whole duration of college, (c) higher add-on for the federal student loan interest rate, (d) non-enrollees' expected likelihood of BA attainment used as beliefs targets, (e) flat income taxation, (f) college tuition depends on skill, (g) lower uptake cost for private loans, (h) college enrollment option shock depends on skill, and (i) skill does not depend on parental education. Each variation of the baseline model is re-calibrated.