Racial Gaps in Student Loan Repayment and Default: A Life Cycle Approach*

Kartik Athreya† FRB Richmond

Christopher Herrington ‡ Virginia Commonwealth University

Felicia Ionescu§ Federal Reserve Board

Urvi Neelakantan¶ FRB Richmond

February 14, 2023

Abstract

Student loan default rates are significantly higher for Black borrowers than for White borrowers and this gap persists when controlling for education attainment. Black college graduates are four times more likely than White graduates to default on student loans while non-graduates are only about twice as likely to default. This is despite the fact that the distribution of loan amounts is similar across Black and White borrowers and that monthly student loan payments are often smaller for Black individuals since they are more likely to enroll in income driven repayment plans. To what extent can observable differences in financial circumstances account for the racial gap in student loan default rates? Are the factors driving the gap similar for college graduates and non-graduates? Does the financial burden associated with student debt affect choices later in life in the same way across the two groups? To address these questions, we construct a life cycle consumption-savings model that captures observed heterogeneity in initial wealth, human capital risk, student loan debt and repayment choices, earnings processes, including racial wage discrimination, and unobserved heterogeneity at the time of labor market entry. We use our model to quantify the degree to which each of these channels contributes to the observed gap in Black-White student loan default rates over the life cycle.

*Preliminary and incomplete.Please do not circulate. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Richmond or the Federal Reserve System.

†Federal Reserve Bank of Richmond, Kartik.Athreya@rich.frb.org

‡Virginia Commonwealth University, herringtoncm@vcu.edu

§Board of Governors of the Federal Reserve System, felicia.ionescu@frb.gov

¶Federal Reserve Bank of Richmond, Urvi.Neelakantan@rich.frb.org

1 Introduction

Black student loan holders are more likely to default than their White counterparts. For both college graduates and non-graduates, racial gaps in default rates appear immediately after student loan borrowers begin repayment and widen continuously over the life cycle. This is despite the fact that the distributions of the amount borrowed at the outset are similar for Black and White individuals, and that Black borrowers are more likely to enroll in income-based or extended repayment plans, which offer smaller monthly payments. Perhaps even more surprisingly, the racial default rate gap is larger for college graduates than for college non-graduates: Black college graduates are four times more likely than White graduates to default on student loans while Black non-graduates are about twice as likely to default.

In this paper, we ask whether financial circumstances over the life cycle can account for the racial gaps in repayment and default. Intuitively, the well-documented differences in life cycle earnings between Black and White individuals should play a role. For example, Black workers have lower average earnings and lower earnings growth than White workers with the same education level. Moreover, Black workers face greater earnings risk, so earnings uncertainty may also affect loan repayment decisions. In addition, wealth holdings of Black and White households likely also contribute to differences in ability to repay. Given differences in wealth and earnings, even with similar student debt levels, the financial burden associated with student debt may affect groups of borrowers in a different way in terms of decisions they make later in life, such as human capital investment and financial asset accumulation. In turn, these decisions will affect how earnings and wealth evolve over the life cycle. These too may help account for default rate differences.

To quantify the relative contribution of these factors to the Black-White gap in student loan default rates, we build a life cycle consumption-savings model with a rich menu of student loan repayment plans and a default option along with key choices individuals make over the life-cycle: human capital investment, labor supply, investment in financial assets and borrowing. A crucial modeling feature for the question at hand is that we allow for group specific heterogeneity in initial characteristics, including student debt, initial financial assets as well as unobservable characteristics, such as ability and human capital stock. Furthermore, individuals face group specific idiosyncratic risks to human capital investment. Lastly, we explicitly model racial wage discrimination, a key ingredient of our analysis since discrimination reduces the measured earnings of Black workers relative to White workers with equivalent human capital and labor supply.

We calibrate the model in a series of steps. After setting some standard parameters exogenously, we estimate a set of parameters specific to each of the four groups: Black college graduates, White college graduates, Black non-graduates and White non-graduates. These parameters will govern model elements which are directly observable in the data: initial financial assets, initial student debt distributions, earnings dynamics, human capital risk, income replacement rates in retirement, and unsecured credit limits. Then, we build on the procedure pioneered by Huggett, Ventura and Yaron (2011) to calibrate the joint distribution of unobservable "initial" characteristics at the time of labor market entry to match the mean, dispersion, and skewness of life cycle earnings for each group. An important observation is that without discrimination in the model, our calibration procedure would tend to *underestimate* the initial human capital and learning ability of individuals facing discrimination, as it would naively interpret lower initial earnings as reflecting lower human capital, and lower earnings growth as lower learning ability. With the model calibration thus specified, we study the contribution, in turn, of each of the factors listed above. For instance, to evaluate the importance of initial financial wealth, we compare default rates in the baseline model to the the case in Black college graduates are endowed with the same initial wealth as White college graduates.

Before turning to explaining default and repayment behavior, it is important to first understand the role that student debt burden plays for life-cycle choices. As mentioned, despite similar student debt levels, the financial burden associated with student debt may affect groups of borrowers in a different way given its interaction with financial positions and earnings. We measure the impact of student loan debt by comparing observed human capital, earnings, and wealth accumulation to those occurring when student debt is eliminated. We find that for White individuals, debt relief does not substantially impact human capital accumulation paths. For Black individuals, in contrast, debt relief significantly boosts human capital accumulation and therefore earnings and wealth. The primary driver of these results is the effect of student loan debt on the learning vs. earning tradeoff. For any given marginal product of human capital, nondefaultable debt forces time to be spent earning, not learning. The opportunity cost of that time is proportional to the marginal product of human capital. In this instance, the marginal product of human capital is, on average, lower for White individuals than Black individuals, leading to smaller changes in outcomes for learning in the wake of debt relief.

Our paper is structured as follows. We begin in Section 2 by describing facts about student loan debt and default for Black and White borrowers. Next, in Section 3 and 4, we develop a structural life cycle model of consumption, savings, and debt repayment and calibrate it to match the facts. In Section 5, we use the model to understand how earnings, initial wealth, and the choice of student loan repayment plan contribute to default behavior.

2 Data

2.1 Student Loan Debt, Repayment, and Default

We motivated this paper with the observation that student loan default rates are higher for Black borrowers than White borrowers. Figure 1 documents this fact using data from the Beginning Postsecondary Students (BPS) 1996 survey.[1] Within 20 years of entering repayment, around 20 percent of White borrowers have ever defaulted on their loans, compared to nearly 50 percent of Black borrowers.

Figure 1: Student Loan Default Rates by Race

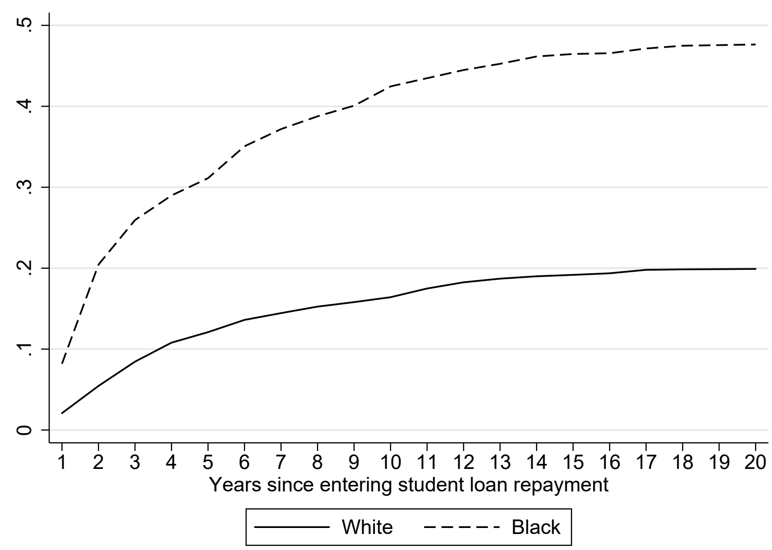
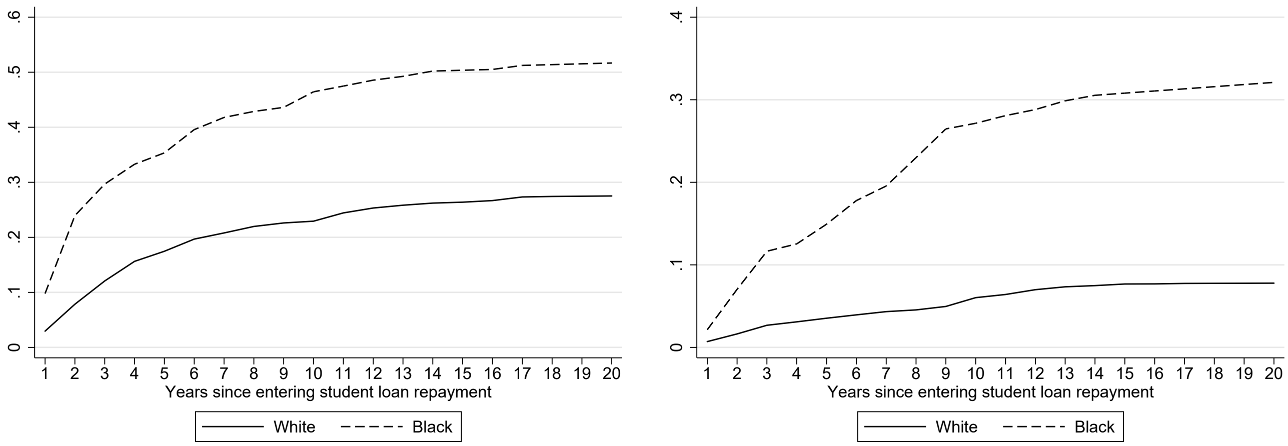


Figure 2 shows student loan default rates by race and educational attainment. While default rates are lower for graduates than non-graduates, the racial gap is larger for the former group. Figure 2a shows that the Black default rate is about twice as high as the White default rate for non-graduates, while Figure 2b shows that it is four times as high for college graduates. This affects a nontrivial fraction of the population: Overall, 80.1% of Black graduates have student loans, compared with 58.6% of White graduates. Borrowing is somewhat less common for non-graduates, yet still high, and the Black-White gap is also slightly smaller.

[1] All results in this section were calculated using the National Center for Education Statistics DataLab tool at `https://nces.ed.gov/datalab`. Individuals in these data were first-year college students in the 1995–96 academic year when they were first surveyed as part of the National Postsecondary Student Aid Survey (NPSAS). Subsequent surveys in 1998 and 2001, combined with the 2015 Federal Student Aid Supplement allow us to obtain information about borrowing, repayment, and default choices up to 20 years after they started college.

Figure 2: Student Loan Default Rates by Race and Educational Attainment



(a) Non-graduates

(b) Graduates

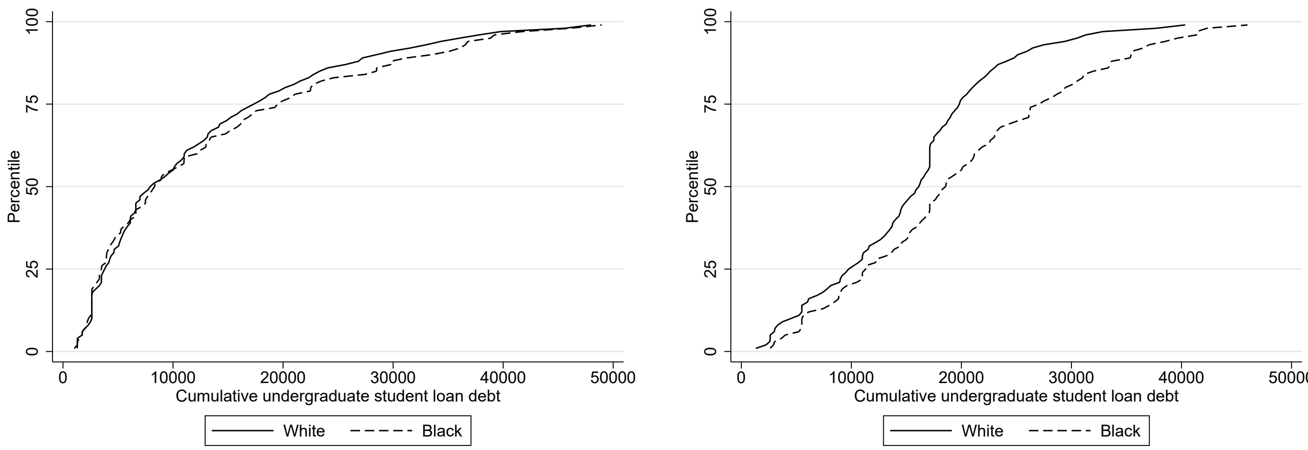
What could account for the racial differences in default rates? We begin by looking at student loan borrowing behavior. Table 1 summarizes several key facts by race and college completion status. First, conditional on borrowing, Black graduates borrow more on average than White graduates, though the difference is small for non-graduates. Interestingly, as Figure 3 shows, Black and White borrowers have similar cumulative distributions of undergraduate student debt, especially among non-graduates. Despite having greater average student loan debt, however, Black borrowers have slightly smaller average monthly payments because they are more likely to be enrolled in non-standard repayment plans with extended timelines or income-based payments.

Table 1: Summary Statistics: Beginning Postsecondary Students 1996 cohort

	Graduates			Non-graduates		
	All	White	Black	All	White	Black
Share borrowing (%)	60.8	58.6	80.1	48.1	45.1	62.7
Mean cumulative loans ($, as of 2015)	15,897	15,575	19,836	12,268	12,225	13,103
Avg monthly payment ($, as of 2001)	204	205	183	134	135	117
Share with loans fully paid by 20 years (%)	48.8	51.1	17.3	43.2	47.7	28.1
Avg amount owed/borrowed at 20 years (%)	79.8	73.1	113.6	101.7	98.1	114.6
Share ever in default by 20 years (%)	9.9	7.8	32.1	33.8	27.5	51.7

Differences in borrowing and repayment choices during and shortly after college manifest as much larger differences later in the life cycle. For example, using the 2015 supplement we find that 51.1% of White college graduates have fully paid off their student loans within 20 years of first starting college, compared to only 17.3% of Black graduates. Moreover, when we consider those with loans still outstanding, we find that Black borrowers, on average, owe *more* after 20 years that the original amount borrowed, which is not the case for White borrowers.

Figure 3: Cumulative Distributions of Student Debt



(a) Non-graduates (b) Graduates

To summarize, Black individuals are far more likely to have taken out student loans than their White counterparts. Conditional on borrowing, Black student borrow more that White students. Yet, Black borrowers make smaller monthly student loan payments than White borrowers because they are more likely to be enrolled in non-standard repayment plans. Finally, Black borrowers are more likely to default on their student loans than White borrowers, and the racial default gap is larger for college graduates than non-graduates. Intuitively, it is likely that earnings and wealth differences play an important role in the racial differences in student loan borrowing, repayment, and default behavior. We document these differences in the next section.

2.2 Life Cycle Earnings

We construct life cycle profiles of earnings statistics using data from the Current Population Survey (CPS), obtained through IPUMS at the University of Minnesota (Flood et al., 2021). We impose several sample restrictions. We limit the sample to the 1968-2013 survey years to ensure consistency in the earnings and weighting variables. We use weights to ensure that each year's sample is representative of the US population. Additionally, we renormalize the weights to keep the population constant at its 2014 level. Given our interest in college enrollees, we exclude those who never enrolled in college. To focus on observations after individuals leave college, we focus on those aged to those aged 25 and over. We look at earnings throughout working life, which we assume ends at age 66 with retirement. Finally, we exclude those who earned less than $1000 (in 2019 dollars).

The CPS is not a panel, so it does not allow us to directly observe the profile of earnings over the life cycle. Earnings differences across individuals could be the result of time effects (e.g, aggregate fluctuations), cohort effects (lifetime experiences that vary by birth year) or age effects (e.g., experience). We need to distinguish the latter from the first two effects. The three are perfectly collinear, so we impose the identifying assumption that cohort effects are zero.

For each year between 1968 and 2013, we calculate the mean, skewness, and Gini of earnings by race and educational attainment, which are the moments we will target later in calibrating the quantitative model. To obtain the life cycle profiles of these moments, we regress each of these in turn on a cubic in age with a birth cohort dummy, where each birth cohort is a five-year period between 1905 and 1990. The resulting estimates are displayed in Figure 4. The gap in earnings over the life cycle between Black and White individuals is evident among both college graduates (CG) and non-graduates (NG), though it is larger for the latter. At their peak, mean earnings of White college graduates are over 30 percent higher than the mean earnings of Black college graduates.

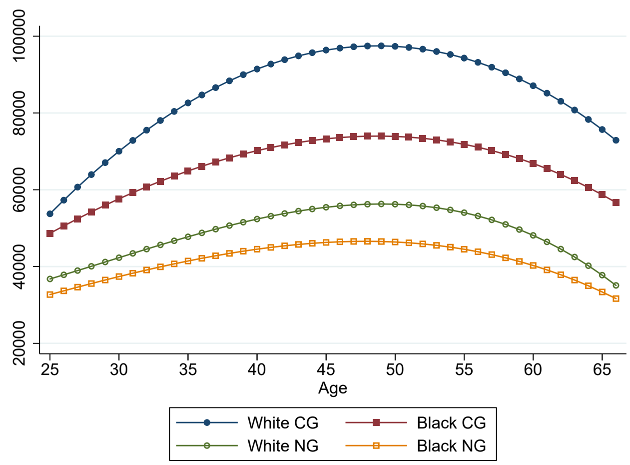
Figures 4b and 4c show additional interesting patterns across groups. For example, skewness is highest among White college graduates for most of the lifecycle, but in the last few years of working life it is highest among Black non-graduates. Our measure of inequality, the Gini coefficient, is highest among White graduates for almost the entire lifecycle, followed closely by White non-graduates. Interestingly, inequality is almost always lowest among Black college graduates.

2.3 Initial Wealth

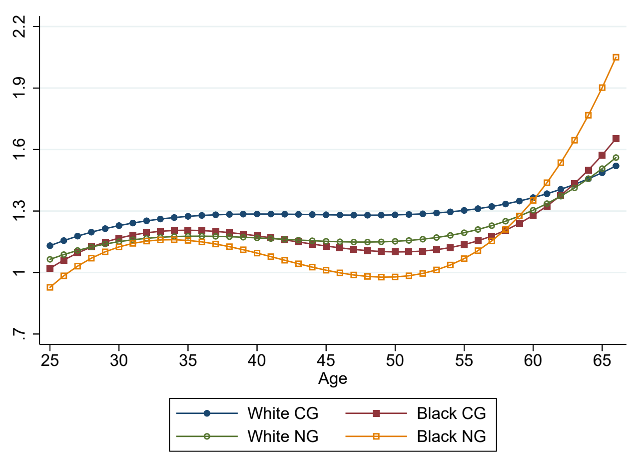
Next, we utilize the Survey of Consumer Finances (SCF) to establish facts about the wealth levels of Black and White households around the time when they first enter the labor market, which we will refer to as their "initial wealth". To obtain sufficiently large samples by race and educational attainment, we combine SCF waves from 1989–2019 and adjust all nominal values to 2019 dollars using the CPI.

Table 2 summarizes the distribution of initial wealth by race and educational attainment in the SCF. We present two measures of wealth: total assets and net worth (total assets minus total debt). For ease of comparison, we normalize each statistic (i.e., each row in the table) relative to

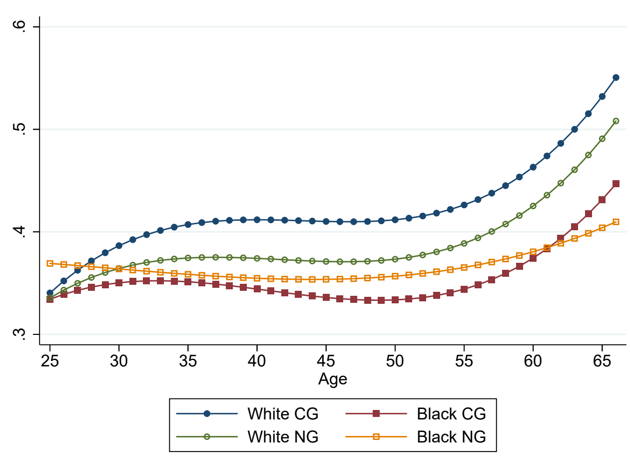
Figure 4: Life Cycle Earnings Statistics



(a) Mean



(b) Skewness



(c) Gini

White college graduates. Several key takeaways are immediately apparent. First, Black college graduates hold fewer total assets than White graduates, both at the mean and the median. For non-graduates, however, the comparison is more complicated. Black non-graduates have slightly higher mean assets, but their *median* value is much smaller.

Table 2: Wealth Statistics by Race and Educational Attainment

		Graduates		Non-graduates	
		White	Black	White	Black
	Mean	1.00	0.62	0.56	0.59
Assets:	Median	1.00	0.53	0.51	0.24
	S.D.	1.00	1.26	0.45	1.13
	Mean	1.00	0.43	0.58	0.84
Net Worth:	Median	1.00	-0.13	0.56	0.06
	S.D.	1.00	1.26	0.45	1.17

When we consider net worth instead of total assets, we find similar results. On average, Black graduates have less than half the net worth of White graduates. Moreover, the median net worth for Black graduates is actually negative. Black non-graduates also have very little net worth at the median, but their mean net worth exceeds that of White non-graduates. In the case of both wealth measures—assets and net worth—the standard deviation is higher among Blacks than Whites, and lower among non-graduates compared to graduates.

3 Model

3.1 Environment

We construct a life cycle economy populated by individuals who begin life as college graduates or non-graduates and live till age T. Time is discrete and indexed by $t = 1, ..., T$ where $t = 1$ represents the first year after leaving college. Agents differ in their learning ability, a, which is no longer mutable once they enter the model. They also differ in their initial endowments of human capital, h_1, and wealth x_1.[2] These characteristics are drawn jointly according to a distribution

[2]We assume, as is standard in Ben-Porath models, that learning ability is fixed over time for each agent. In other words, by the time agents enter the model, they have learned as much as they can about *how to learn*. Ability reflects learning tools and skills conferred on the young and, in sum, measures the effectiveness with which an individual can turn time into human capital. In contrast, initial human capital represents the actual stock of

$F_i(a, h, x)$ on $A \times H \times X$, where i indicates that the distribution will vary across identifiable groups in the data. For our purposes, i will represent four groups: White and Black college graduates, and White and Black non-graduates. Individuals also differ in the amount of student loans they took out to finance their college education, $d(x_1)$, which is assigned according to an exogenous distribution, $G_i(d/x_1)$on $D = [0, \overline{d}]$.[3]

Our model is a generalization of the human capital model developed by Ben-Porath (1967) and updated by Huggett, Ventura and Yaron (2006), which we extend to capture joint decisions in the labor market and in the student loan market, closely following Ionescu (2009). Specifically, each period, agents choose how much to consume and how to divide their one unit of time between learning and earning, as in Ben-Porath (1967). The time devoted to learning is denoted by l. Agents work and accumulate human capital using the Ben-Porath technology until $t = J$.

We also incorporate financial portfolio choices over the lifecycle, as in Athreya, Ionescu and Neelakantan (2023). Individuals can choose to accumulate wealth and divide their asset holdings between a risk-free asset or a risky assest (e.g., stocks). They can also borrow in an an unsecured consumer credit market. This debt, which is separate from the aforementioned student loan debt, is not defaultable and is subject to a borrowing limit, $-\underline{b}_i$, where $\underline{b}_i > 0$ and may differ across groups.

Individuals who have student debt face a menu of repayment plans and decide whether to repay or default. Repayment plans and default consequences are modeled to mimic the existing U.S. student loan system. As in practice, individuals with student debt are initially assigned a standard repayment plan which assumes a fixed payment amount, $\bar{p}$, each period for 10 periods. Agents have the choice to remain under the standard repayment plan, switch to an income contingent repayment plan or to default. Agents retire in period $t = J + 1$, after which they face a simple consumption-savings and portfolio choice problem.

The optimal life cycle problem is solved in two stages. First, for each repayment plan and the default option, we solve for the optimal path of consumption, time allocation, and human capital investment. Individuals then select between staying under the standard, switching to the income contingent repayment plan or default. This choice is available as long as agents stay under the standard repayment plan.

---

learning accumulated by the time the agent completes college, which may be the result of investments made in the individual's human capital by their parents, the school system, and the community at large. Since learning is lifelong, human capital can increase over the course of the agent's life as long as they invest time in it.

[3]In practice, the amount of student loans that students can take out depends on their initial wealth and the cost of college (negatively correlated) and up to a maximum limit.

3.2 Preferences

Individuals derive utility from consumption. Preferences are represented by a standard time-separable constant relative risk aversion (CRRA) utility function with coefficient of risk aversion σ.The agent's problem is to choose consumption over the life cycle, $\{c_t\}_{j=1}^{J}$ to maximize the expected present value of utility over the life cycle,

$$\max \mathbb{E} \sum_{j=1}^{J} \beta^{j-1} \frac{c_j^{1-\sigma}}{1-\sigma}, \tag{1}$$

where β is the discount factor common to all agents.

3.3 Human Capital and Earnings

Agents can invest in their human capital after college by apportioning some of their available time to acquiring additional human capital throughout their working lives. Human capital is risky, which we model by subjecting it to idiosyncratic shocks, z. As in Huggett, Ventura and Yaron (2011), we assume that shocks to human capital are independent and identically distributed over time and follow a group specific normal distribution, $z \sim N(\mu_{i,z}, \sigma_{i,z}^2)$. For an individual agent, human capital evolves as follows:

$$h_{t+1} = exp(z_{t+1})[h_t + a(h_t l_t)^{\alpha}]. \tag{2}$$

Human capital production depends on the agent's learning ability, a, accumulated human capital, h_t, the fraction of time spent on human capital accumulation, l_t, and the production function elasticity, α.

Our approach aims to capture a prominent risk facing college attendees: whether devoting time fully to learning will deliver the expected returns to whatever amount of human capital they are ultimately able to acquire, while recognizing the fact that they can further accumulate human capital through on the job training. The addition of student debt also implies risk to future consumption due to the uncertainty of future earnings.

Earnings are a function of the rental rate of human capital, w_t, the agent's human capital, h_t, and the time spent in market work, $(1 - l_t)$. Earnings grow at the rate g_i and evolve stochastically because human capital is risky. Finally, we also allow for racial wage discrimination in the labor market. Specifically, the rental rate of human capital is discounted by a fraction $\theta_i \leq 1$ for individuals in group i.

3.4 Means-tested transfer and retirement income

We allow agents to receive means-tested transfers, τ_t, which depend on age, income, and assets. Following Hubbard, Skinner and Zeldes (1994), we specify these transfers as

$$\tau_t(t, y_t, x_t) = \max\{0, \underline{\tau} - (\max(0, x_t) + y_t)\}. \tag{3}$$

These transfers capture the net effect of the various US social insurance programs that are aimed at providing a floor on income (and thereby on consumption).

After period $t = J$, in which agents start retirement, they receive a constant fraction of their earnings in the last working period, $\varphi_i(y_J + \tau_J)$, which they allocate between risky and risk-free investments. We allow the income replacement rate φ_i to vary across groups.

3.5 Financial markets

Households have access to a risk-free asset b_t, which we interpret as savings (or borrowing when negative), and a risky asset s_t, which we interpret as stocks. Saving ($b_t > 0$) earns the risk-free interest rate, R_f, while borrowing ($b_t < 0$) represents unsecured credit and incurs an additional cost. Following Davis, Kubler and Willen (2006) we model this as a proportional cost, denoted by ω, which captures the costs of intermediating credit. The borrowing rate, R_b, therefore, is higher than the risk-free savings rate: $R_b = R_f + \omega$.

Stocks earn a stochastic return $R_{s,t+1} = R_f + \mu + \eta_{t+1}$, where μ is the mean excess return (i.e., the risk premium), and $\eta_{t+1} \sim N(0, \sigma_\eta^2)$ is the independent and identically distributed (i.i.d.) shock to the excess return. Total financial wealth is given by $x_t = R_j b_t + R_{s,t} s_t$, with $R_j = R_f$ if $b_t \geq 0$ and $R_j = R_b$ if $b_t < 0$.

After completing education, individuals start repayment on their student loan according to a standard plan. The interest rate on student loans is denoted R_g and, consistent with the data, we assume $R_f < R_g < R_b$, where R_f is the risk-free savings rate and R_b the borrowing rate on unsecured debt. Students face a menu of repayment options, including default, which we describe in detail next.

3.6 Repayment options and default

3.6.1 Institutional details

Appendix B provides an overview of the student loan program with a focus on federal student loans, the major source of funding for college education in the US. As we describe there, borrowers have several repayment plans to choose from, which can broadly be classified as Standard or Income-Driven Repayment (IDR). The two types of plans differ in three key ways. First the standard plan has a repayment period of 10 years, while the repayment period for IDR plans can extend to 20 years or more. Second, the amortization of the loan into equal monthly payments under the standard plan leads to higher monthly payments than under the IDR plan. While the borrower's income plays no role in the calculation of monthly payments under the traditional plans, all IDR plans calculate payments as a function of the borrower's current income. Finally, the standard plans has no loan forgiveness while IDR plans stipulate that any remaining balance will be forgiven if the loan is not paid in full at the end of the specified term.

Borrowers are considered to be in default if they have not made their scheduled student loan payments for at least 270 days. In this event, the unpaid balance and accumulated interest cannot be discharged and becomes due immediately. To meet this obligation, a portion of the borrower's wages may be garnished or withheld.

3.6.2 Modeling repayment and default

We capture the key features of repayment and default described above as follows. In the model, agents start repaying their loans under the standard plan which assumes a fixed payment each period, p_{SR}. As long as agents do not change this status, given the debt level, earnings, and interest rate they learn at the beginning of each period, they face the following repayment options: (1) keep paying under the standard plan until payment is complete; (2) switch to an income-driven plan that assumes that payments are contingent on income realizations, p_{IR} (income repayment); and (3) default, p_D. Agents cannot switch back to standard repayment after choosing income contingent repayment or default. Once they switch to income repayment, they extend the life of the loan to P' periods ($P' = 20$). Corresponding to the agents' two payment options, there are two types of payments, given by

$$p_{SR} = \frac{d}{\sum_{t=1}^{P} \frac{1}{(R_g)^t}} \tag{4}$$

$$p_{IR_j} = \left\{0, \text{if } y_j \leq \underline{y}\right\}, \text{or} \tag{5}$$

$$\left\{\lambda w_j h_j (1 - l_j), \text{if } y_j > \underline{y}\right\}, \text{for } j = k, ..., P^{'} \tag{6}$$

$$p_{IR_j} = 0, \text{for } j = P^{'} + 1, ..., J \tag{7}$$

In case of standard repayment, the fixed payment is fully determined by the loan size, d, the interest rate on student loans, R_g, and the duration of the loan, $P = 10$ periods. In case of income driven repayment, the payment is given by a fraction λ of the agent's per period earnings as long as the borrower's income is above a poverty threshold, otherwise it is 0. If the loan is not fully repaid after 20 periods since switching to income repayment, which occurs in period $j = k$, the remaining debt is discharged.

In case of default, payments are $p_{D_j} = 0$ in the period $j = q$ when default occurs and $p_{AD_j} = \frac{d(1+\tau)}{\sum_{t=1}^{P} \frac{1}{(R_g)^t}}$ for periods $j = q+1, ..., P$ when borrowers rehabilitate and repay using fixed payments. We model two penalties associated with default: a wage garnishment in the period when default occurs and an increase in the amount due starting the following period after default occurs. While there is no payment during the period in which default occurs, agents start repaying a larger amount, $d_q(1+\chi)$, in the following period. We do not allow for repeated default.[4] Debt evolves according to the equation $d' = (d-p)R_g$ where $p \in P = \{p_{SR}, p_{IR}, p_{AD}\}$ is the payment made in the previous period.

3.7 Agents' Problem

Agents in the model choose how much to consume, how much time to allocate to learning and to market work, and asset position (saving in risk-free assets or borrowing) to maximize expected lifetime utility. During the student loan repayment period, they also choose whether to repay or default on their student debt, and, if repaying, whether to remain under the standard plan or switch to income driven repayment.

We solve the problem backwards, starting with the last period of life when agents consume all their available resources. In the description of the problems below, we suppress the i subscripts for brevity.

The value function in the last period of life is set to $V_T^R(a, h, x) = u(x)$.

3.7.1 Retired Agents' Problem

Retired agents do not accumulate human capital and no longer have student loans to repay. For period $J+1, ..., T$, they face a simple consumption-savings problem and may choose to invest in both risk-free and risky assets. The value function is given by

[4] While it is true that borrowers can default again, in practice, severe punishments imposed on borrowers who choose to repeatedly default induce defaulters to rehabilitate and repay shortly after default occurs. Follow-up studies of defaulters reveal that two out of three defaulters reported making payments shortly after the official default first occurred (Volkwein et al. (1998)). In addition, **?** shows that if repeated default is allowed, the extra default is negligible (less than 1 %). Thus, given the complexity of the current setup, we choose not to model this option for tractability purposes.

$$V^R(t,a,x,y_J+\tau_J) = \max_{b',s'} \left\{ \frac{c^{1-\sigma}}{1-\sigma} + \beta \mathbb{E}_\eta V^R(t+1,a,x',y_J+\tau_J) \right\}, \tag{8}$$

where

$$\begin{aligned} c + b' + s' &\leq \varphi(y_J+\tau_J) + x \\ b' &\geq \underline{b} \\ x' &= R_j b' + (R_f + \mu + \eta) s' \end{aligned}$$

and $R_j = R_f$ if $b \geq 0$, and $R_j = R_b$ if $b < 0$.

3.7.2 Problem in Working Phase

We use $V^R_{i,J}(t,a,x,y_J+\tau_J)$ from the retirement phase as a terminal node and solve for the set of choices in the working phase $t = 1,..,J$ of the life cycle. We further break down the working phase into a student loan post-repayment phase and a repayment phase.

Post-repayment phase In the post-repayment phase, $t_P \in \{P, k+P', q+P\},...,J$, with k switching time to income driven repayment and q time of default, if such choices are made, the problem is simply given by

$$V^{PR}(t,a,h,x,z) = \max_{l,h',b',s'} \left\{ \frac{c_t^{1-\sigma}}{1-\sigma} + \beta \mathbb{E}_{\eta,z'} V^{PR}(t+1,a,h',x',z') \right\} \tag{9}$$

where

$$\begin{aligned} c + b' + s' &\leq \theta w h(1-l) + x + \tau(t,y,x) \text{ for } t = t_P,..,J \\ l &\in [0,1] \\ h' &= exp(z')[h + a(hl)^\alpha] \\ b' &\geq \underline{b} \\ x' &= R_j b' + (R_f + \mu + \eta) s' \end{aligned}$$

and $R_j = R_f$ if $b \geq 0$, and $R_j = R_b$ if $b < 0$.

Repayment phase In the repayment phase, as long as agents do not switch to the income repayment plan or default, all options are available to them until the loan is paid in full. Hence, for every period before P, the agent can choose between continuing to be on standard repayment, switching to income repayment, or default. Once agents switch to income repayment or default, they cannot switch back. Therefore, in the repayment phase, agents can be under one of the following three cases:

Case 1: Repayment under the standard plan Agents are in this stage for $t = 1, ..., P$ periods if they do not switch to income driven repayment or default. Therefore, they repay their student loans with a fixed per-period payment, which is determined by the size of the loan, the duration of the loan, and the interest rate on student loans.

The value function is given by

$$V^{SR}(t,a,h,x,z,d) = \max_{l,h',b',s'} \Big\{ \frac{c_t^{1-\sigma}}{1-\sigma} + \beta \mathbb{E}_{\eta,z'} \max[V^{SR}(t+1,a,h',x',z',d'), \\ V^D(t+1,a,h',x',z'), V^{IR}(t+1,a,h',x',z')] \Big\} \tag{10}$$

where

$$\begin{aligned} c + b' + s' &\leq \theta wh(1-l) + x + \tau(t,y,x) - p \text{ for } t = 1,..,P \\ l &\in [0,1] \\ h' &= exp(z')[h + a(hl)^\alpha] \\ d' &= (d-p)(1+r_g), \;\; p \in P, \;\; t = 1,2,...,P \\ b' &\geq \underline{b} \\ x' &= R_j b' + (R_f + \mu + \eta)s' \end{aligned}$$

and $R_j = R_f$ if $b \geq 0$, and $R_j = R_b$ if $b < 0$.

Case 2: Repayment under the income plan Payments are set as a fraction, γ, of earnings if the borrower's income is above the poverty line, i.e. if $\lambda w_j h_j (1 - l_j), \text{if} y_j > \underline{y}$, and 0 otherwise. Payments continue until the loan is repaid in full or for $P' = 20$ years after enrolling in the IDR plan, whichever comes first. After this time, the remaining debt is discharged.

$$V^{IR}(t,a,h,x,z,d) = \max_{l,h',b',s'} \left\{ \frac{c_t^{1-\sigma}}{1-\sigma} + \beta \mathbb{E}_{\eta,z'} V^{IR}(t+1,a,h',x',z',d') \right\} \tag{11}$$

where

$$\begin{aligned} c+b'+s' &\leq \theta wh(1-l)(1-\gamma)+x+\tau(t,y,x) \text{ for } t=k,..,P' \\ l &\in [0,1] \\ h' &= exp(z')[h+a(hl)^{\alpha}] \\ d' &= (d-p_{IR})(1+r_g),\ d>0 \\ b' &\geq \underline{b} \\ x' &= R_j b' + (R_f+\mu+\eta)s' \end{aligned}$$

and $R_j = R_f$ if $b \geq 0$, and $R_j = R_b$ if $b < 0$.

Case 3: Default Agents do not make any payment during the period in which default occurs, and they start repaying their loan during the following period. In the period after default occurs, at $j = q$, the borrower enters repayment under a reorganization plan. In addition to the increase in his debt (χ), there is also a garnishment of part of the defaulter's earnings (ρ). Defaulters are not excluded from the risk-free market, so they can still save and borrow. V^D represents the value function for the period in which default occurs, and V^{AD} represents the value function for periods after default, when reorganization and rehabilitation is required.

$$V_i^D(t,a,h,x,z,d) = \max_{l,h',b',s'} \left\{ \frac{c_t^{1-\sigma}}{1-\sigma} + \beta \mathbb{E}_{\eta,z'} V^{AD}(t+1,a,h',x',z',d') \right\} \tag{12}$$

where

$$\begin{aligned} c+b'+s' &\leq \theta wh(1-l)(1-\rho)+x+\tau(t,y,x) \text{ for } t=q \\ l &\in [0,1] \\ h' &= exp(z')[h+a(hl)^{\alpha}] \\ d' &= d(1+\chi)(1+r_g),\ d>0 \\ b' &\geq \underline{b} \\ x' &= R_j b' + (R_f+\mu+\eta)s' \end{aligned}$$

$$V^{AD}(t,a,h,x,z,d) = \max_{l,h',b',s'} \left\{ \frac{c_t^{1-\sigma}}{1-\sigma} + \beta \mathbb{E}_{\eta,z'} V^{AD}(t+1,a,h',x',z',d') \right\} \text{ for } t=q+1,..,P \tag{13}$$

where

$$
\begin{aligned}
c + b' + s' &= \theta w h(1-l) + x + \tau(t, y, x) - p_{AD} \\
l &\in [0, 1] \\
h' &= exp(z')[h + a(hl)^{\alpha}] \\
d' &= (d - p_{AD})(1 + r_g),\ d > 0 \\
b' &\geq \underline{b} \\
x' &= R_j b' + (R_f + \mu + \eta)s'
\end{aligned}
$$

and $R_j = R_f$ if $b \geq 0$, and $R_j = R_b$ if $b < 0$.

Optimal repayment implies maximizing over these value functions. We solve for optimal choices within each of the three options (continuing under the standard repayment, switching to income repayment or default) paths and then dynamically pick the optimal repayment choice, $p^*(a, h, x, d, j)$, $\forall t = 1, ..., P$.

4 Mapping the model to the data

We have two sets of parameters in our model: those that are common to all four groups and those that are group-specific. Our approach involves a combination of setting some parameters to values that are standard in the literature, calibrating some parameters directly to data, and jointly estimating the parameters that we do not observe in the data by matching moments using several observable implications of the model.

4.1 Common Parameters

Table 3 lists the parameters that are common to all four groups in our analysis. We discuss each of these in turn below.

Timing and preference parameters There are 54 periods in the model where each period is a year. The first 34 years represent the working phase and the remaining 20 correspond to the retirement phase of the life cycle.

The per period utility function is CRRA as described in the model section. We set the coefficient of risk aversion, $\sigma = 2$, which is consistent with values found in the literature.

The discount factor $\beta = 0.96$ is also standard in the literature.

Table 3: Parameters Common to All Groups

Parameter	Description	Value
T	Model periods (years)	54
J	Working periods	34
β	Discount factor	0.96
σ	Coefficient of risk aversion	2
α	Human capital elasticity	0.7
$\underline{\tau}$	Minimal income level	$\$17,936$
R_f	Risk-free rate	1.02
R_b	Borrowing rate	1.11
μ	Mean equity premium	0.06
σ_n	SD of shocks to risky asset	0.157
P	Standard repayment period	10
P'	Income-based repayment period	20
R_g	Student loan rate	1.04
γ	IBR payment as fraction of earnings	0.10
$\underline{y}$	IBR income threshold	TBD
ρ	Wage garnishment under default	0.10
χ	Increase in debt under default	TBD

Human capital and income parameters We set the elasticity parameter in the human capital production function, α, to 0.7. Estimates of this parameter are surveyed by Browning, Chiappori and Weiss (2014) and range from 0.5 to 0.9. The income floor is \$17,936.

Financial markets parameters We turn now to the parameters in the model related to financial markets. The risk-free rate is $R_f = 1.02$, consistent with values in the literature (McGrattan and Prescott, 2000) while the wedge between the borrowing and risk-free rate is $\phi = 0.09$ to match the average borrowing rate of $R_b = 1.11$ (Board of Governors of the Federal Reserve System, 2014).

Student loan program parameters For the student loan program, we first take several parameters directly from their statutory values. The student loan limit is set to d_{max} =\$57,000, the combined limit for subsidized and unsubsidized federal student loans. The standard and income-based repayment timelines are set to $P = 10$ and $P' = 20$, respectively. The interest rate on student loans is set to $R_g = 1.04$, which was the average rate on both subsidized and unsubsidized Federal student loans since 2015. The income-based payment is set at 10% of earnings. We set μ, the increase in debt that occurs under default, to match the average loan balance increase observed in the data pre- and post-default. Finally, we choose the wage garnishment rate ρ so that the model generates the default rate matching the data.

4.2 Group-Specific Parameters

We calibrate group-specific parameters in two steps. First, we either take group-specific parameters directly from the data or estimate such parameters outside of the model to match observable data moments. These relate to the initial wealth distribution, the human capital risk and earnings process, the income replacement rate in retirement, and wage discrimination and initial student loan distributions. Importantly, we jointly calibrate group-specific parameters for the unobservable initial distributions of human capital and learning ability within the model to match life-cycle earnings moments (mean, skewness, Gini). Life cycle estimates of these moments are obtained using the methodology outlined in the Appendix. Figure 4 reports the estimates. In this step we also pin down the correlations between unobserved and observed initial characteristics. Table 4 summarizes all group-specific parameters, and we discuss them in turn below.

Income parameters The rental rate of human capital in the model evolves according to $w_{i,t} = (1 + g_i)^{t-1}$. The growth rate g_i is calibrated to match the average growth rate in mean earnings observed for each group in the data shown in Figure 4a. We obtain 0.01 for Black individuals

Table 4: Group-Specific Parameter Values

		College graduates		Non-graduates	
Parameter	Description	White	Black	White	Black
	Panel A: Parameters estimated outside the model				
g	Growth of human capital rental rate	0.0014	0.0013		
μ_z	Mean human capital shock	-0.022	-0.019		
σ_z	SD of human capital shock	0.105	0.110		
φ	Fraction of income in retirement	0.40	0.49	0.47	0.52
μ_x	Mean initial wealth	\$88,080	\$37,901	\$51,093	\$74,062
σ_x	SD of initial wealth	\$761,556	\$956,280	\$343,032	\$891,871
$\underline{b}$	Consumer credit limit	\$38,400	\$21,425	\$25,253	\$13,030
θ	Wage discrimination	1.00	0.88	1.00	0.88
	Panel B: Parameters jointly calibrated within the model				
μ_a	Mean learning ability	0.35	0.20		
σ_a	SD of learning ability	0.36	0.29		
μ_h	Mean initial human capital	65.2	45.5		
σ_h	SD of initial human capital	60.9	40.6		
ϱ_{ah}	Correlation of (a, h)	0.57	0.61		
ϱ_{ax}	Correlation of (a, x)	0.54	0.18		
ϱ_{hx}	Correlation of (h, x)	0.47	0.15		

and 0.02 for Whites. To set the wage discrimination parameter we normalize $\theta_i = 1$ for White graduates and non-graduates alike. We then estimate θ_i for Black graduates and non-graduates, to match the average Black-White earnings gap over the working life, given the growth rates of rental rate of human capital for the two groups estimated from the data. We obtain $\theta_i = 0.88$ that matches the 15% gap over the working life, which is consistent with estimates from the empirical literature (see and Fryer, Pager and Spenkuch (2013)), as well as the survey articles mentioned previously.

We set retirement income to be a constant fraction of labor income earned in the last year in the labor market. Following Cocco (2005), we set this fraction to 0.93 for college graduates and 0.67 for non-graduates.

Following Guner, Kaygusuz, and Ventura (2014), we set the parameters of the function governing income taxes as follows: $\kappa_0 = 0.264$, (which would be the tax rate if taxes were strictly proportional), $\kappa_1 = 0.964$ (which governs the progressivity of the tax schedule) and $\kappa_2 = 0.012$, which is the scale parameter.

Human capital risk We follow Huggett, Ventura and Yaron (2011) in setting the parameters for the shocks to human capital. We assume that $z \sim N(\mu_z, \sigma_z^2)$. We set $\sigma_z = 0.105$ for White graduates and $\sigma_z = 0.110$ for Black (which implies that a one standard deviation shock moves wages by about 10.4 percent and 11 percent, respectively). To set the mean human capital shock, we note that when agents make no investment in human capital (as is the case for older agents), the ratio of mean earnings from two adjacent periods is $(1+g)e^{\mu+\frac{\sigma^2}{2}}$. Using this expression (along with the values for g and σ_z), we calculate $\mu_z = -0.022$ for White and $\mu_z = -0.019$ for Black graduates.

Initial wealth and consumer credit limits We use the SCF data to set the initial distribution of financial wealth and consumer credit limits for each group. For now, we assume a uniform credit limit across households. The SCF reports, for all individuals who hold one or more credit card, the total of their credit limits. We take the average of this over all individuals in our sample and obtain a value of approximately $18,000 in 2019 dollars. Note that, when we take the average, we include those who do not have any credit cards. This ensures that we are not setting the overall limit to be too loose.

To obtain the moments of the initial wealth distribution, we restrict the SCF sample to those aged 27 or less. The SCF reports net worth at the household level but, because our model is one of individuals, we divide net worth by two in all instances where the respondent is married or living with a partner. We calculate the mean and standard deviation separately for Black and White respondents to obtain the numbers reported in Table 4.

Initial student loan debt We estimate group-specific student loan distributions using data from the BPS, as described in Section 2.1. Specifically, for each of the four groups, we feed into the model that group's empirical cumulative distribution of student loan debt shown in Figure 3.

Initial distributions: learning ability and human capital For each racial group, the parameters of the distribution of initial characteristics (learning ability and human capital) are estimated to match the evolution of three moments of the earnings distribution over the life cycle documented earlier (mean earnings, the Gini coefficient of earnings, and the skewness of earnings, i.e., the ratio of mean to median earnings). Since a key goal of this paper is to measure contributing factors to default patterns across groups, how we arrive at the distribution of initial heterogeneity for each group is important. In this we employ the strategy pioneered in Huggett, Ventura and Yaron (2006), who show that a joint lognormal distribution that allows for heterogeneity in both learning ability and human capital, as well as a correlation between the two, matches properties of US earnings data well. Furthermore, Huggett, Ventura and Yaron (2006) prove that heterogeneity in learning ability is necessary and demonstrate that heterogeneity in initial human capital and a positive correlation between the two are important to match properties of the earnings distribution over the entire life cycle. Following their methodology, we restrict the initial distribution to lie on a two-dimensional grid spelling out human capital and learning ability. The underlying joint lognormal distribution is characterized by five parameters: the mean and standard deviation of learning ability and initial human capital, respectively, and the correlation between the two.[5] We then search over the vector of parameters that characterize the initial state distribution to minimize a distance criterion between the model and the data. Specifically, we find the vector of these parameters $\Gamma = (\mu_a, \sigma_a, \mu_h, \sigma_h, \varrho_{ah})$ as well as correlations ϱ_{ax} and ϱ_{hx} by solving the minimization problem:

$$\min_{\Gamma} \left(\sum_{j=5}^{J} |log(m_j/m_j(\Gamma))|^2 + |log(d_j/d_j(\Gamma))|^2 + |log(s_j/s_j(\Gamma))|^2 \right),$$

where $m_j, d_j,$ and s_j are the mean, dispersion, and skewness statistics constructed from the CPS data on earnings, and $m_j(\Gamma)$, $d_j(\Gamma)$, and $s_j(\Gamma)$ are the corresponding model statistics.[6] Panel B of Table 4 shows the moments of these distributions as well as the correlations between unobserved characteristics and initial wealth. An interesting implications is that the correlations with initial wealth are much larger in the case of White college graduates than in the case of Black college graduates.

4.3 Model fit

4.3.1 Targeted moments

We present the model predictions for targeted data moments for the baseline economy, calibrated to White college graduates as well as for the economy calibrated to Black college graduates and discuss goodness of fit for the two calibrated economies.

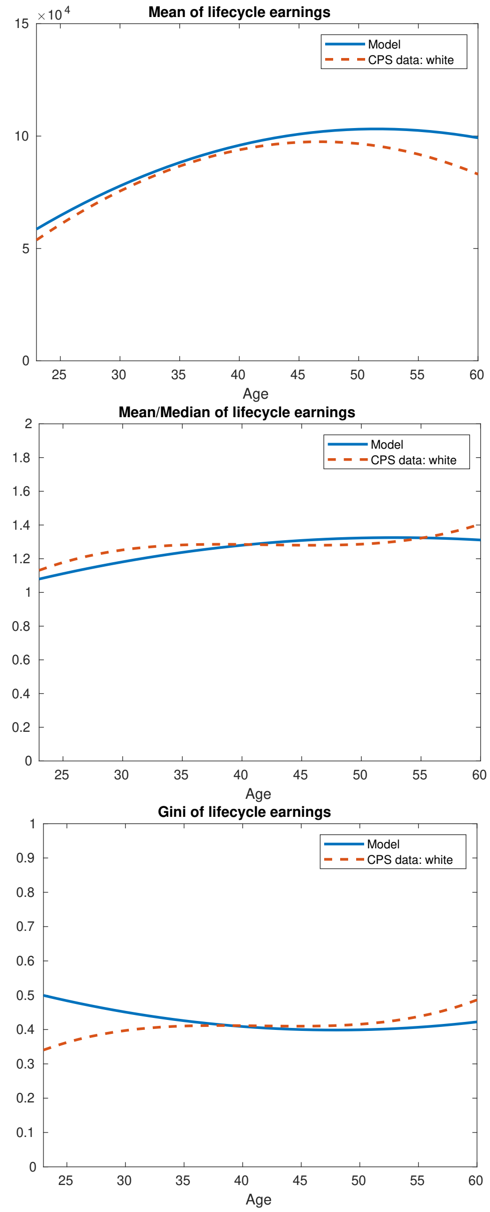
Figure 5 shows the earnings moments for a simulated sample of individuals in the model versus the CPS data for White college graduates and Figure 6 shows the counterpart of these earnings moments for Black college graduates.[7] As these figures show, the model does a reasonably good job of fitting the evolution of earnings paths over the life cycle and their heterogeneity for both groups

[5] In practice, the grid is defined by 20 points in human capital and in learning ability.

[6] For details on the calibration algorithm, see Huggett, Ventura and Yaron (2006) and Ionescu (2009).

[7] As a measure of goodness of fit, we use $\frac{1}{3(J-4)} \sum_{j=5}^{J} |log(m_j/m_j(\gamma))| + |log(d_j/d_j(\gamma))| + |log(s_j/s_j(\gamma))|$. This represents the average (percentage) deviation, in absolute terms, between the model-implied statistics and the data. We obtain a fit of 8 percent (where 0 percent represents a perfect fit).

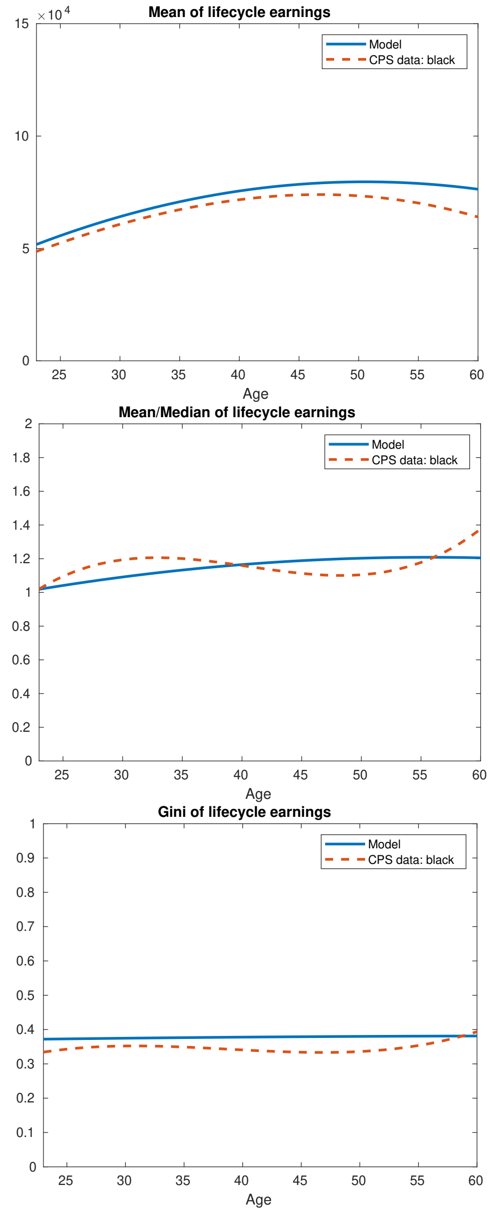
Figure 5: Lifecycle Earnings Statistics: White College Graduates



of college graduates.[8] Importantly, our estimation strategy captures the observed earnings gap between the two racial groups over the entire life-cycle, as shown in Figure 7. On average, White college graduates earn 24 percent more over the life-cycle compared to Black college graduates.

[8]We convert earnings to model units such that mean earnings at the end of working life, which equal $53,134, are set to 100. Because we assume that retirement income is a function of earnings just before retirement, agents in our model have an incentive to maximize pre-retirement earnings. This explains why earnings do not taper off near retirement in our model.

Figure 6: Lifecycle Earnings Statistics: Black College Graduates

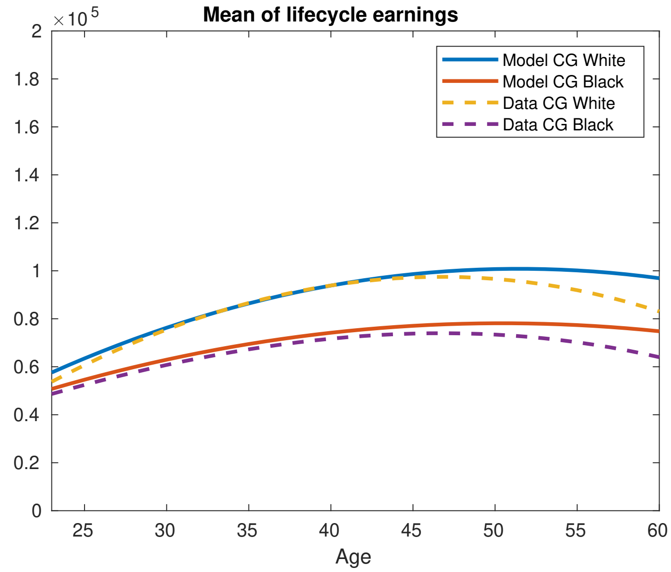


4.3.2 Initial characteristics

We next discuss the implications of our estimation for the joint distribution of initial characteristics for the two groups of college graduates. We take a closer look at the relationship between human capital and learning ability for the two racial groups by comparing the distributions of these two attributes across White and Black college graduates, as well as their correlations with initial wealth.

The panels of Figure 8 display the distributions of human capital and learning ability for the

Figure 7: Lifecycle Earnings Statistics: White College Graduates

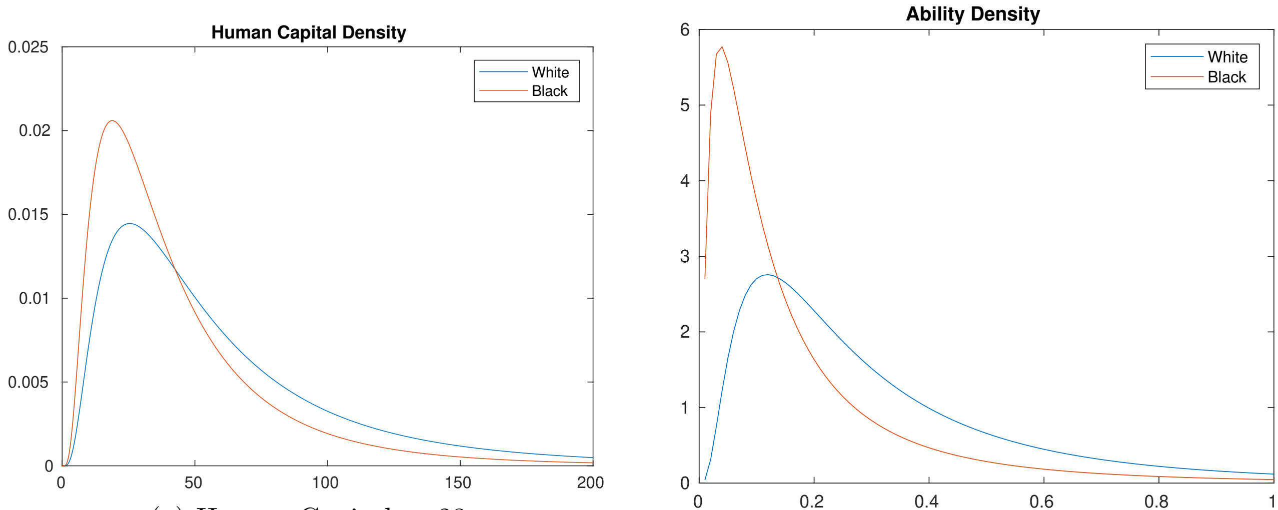


two groups at the beginning of life (age 23). As shown, the distributions of both human capital and learning ability for White are to the right of the distributions for Black college graduates (Figures 8a and 8b). The marginal densities of learning ability and human capital feature a higher mean and larger dispersion relative to Black college graduates. Why does this occur? In general, human capital pins down the levels of earnings whereas learning ability affects the growth of earnings over the life cycle. Since White college graduates have both higher levels and steeper profiles of earnings, this results these differences in initial distributions across the two groups.

5 Results

We first present the predictions of our model for non-targeted outcomes over the life-cycle for both Black and White college graduates and discuss the implications of student debt financial burdens for household decisions across the two racial groups (Section 5.1). We then assess the role of initial conditions for labor and financial market outcomes and discuss the interaction between student debt burdens with initial conditions for household decisions in these markets, including human capital and labor supply as well as financial assets accumulation (Section 5.2). Lastly, we turn to the implications of these interactions for student loan default and repayment behavior and asses the contribution of factors in both financial and labor markets along with initial conditions for the observed default behavior (Section 5.3).

Figure 8: Learning Ability and Human Capital Distributions Across the Two Groups



(a) Human Capital at 23

(b) Learning Ability at 23

5.1 Model predictions

This section presents our model predictions for life-cycle decisions on labor and financial markets across White and Black college graduates and discusses the role played by the financial burden associated with student debt in making such choices.

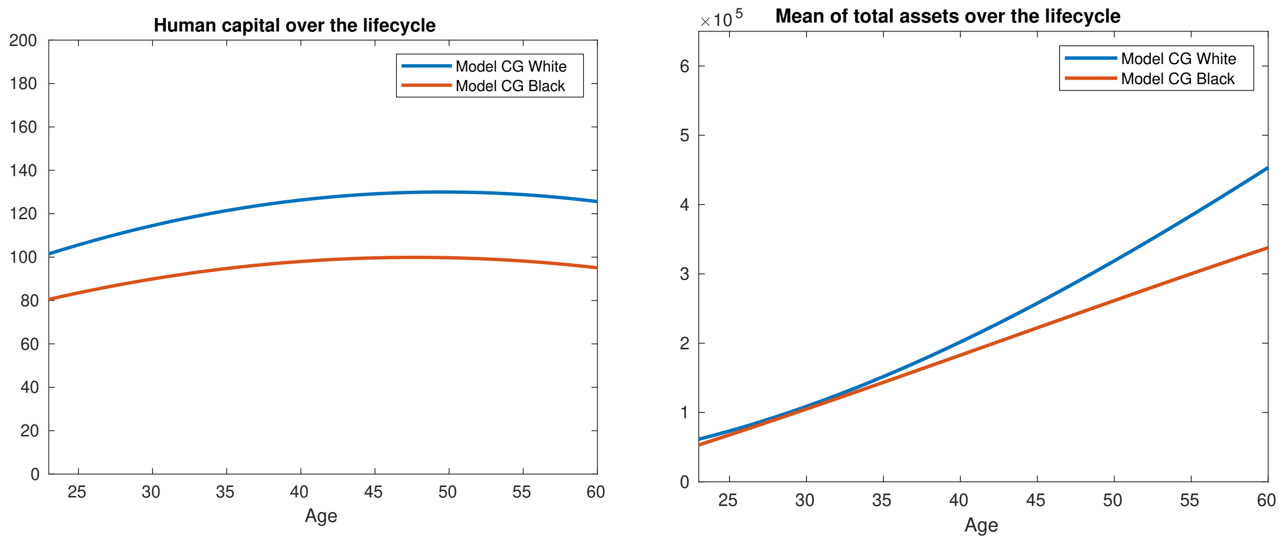
5.1.1 Human capital and financial asset accumulation across groups

We first turn to the model's predictions for human capital and asset accumulation over the life cycle across the two racial groups. Note that none of these facts are targeted by our calibration. The results are shown in Figure 9. The model suggests that the life cycle profile of human capital accumulation are very similar for Black and White college graduates, though the latter accumulate, on average, about 24 percent more human capital than Black college graduates. By comparison, the two groups have nearly identical total assets at the start of the life cycle, but White college graduates accumulate wealth faster, leading to a gap that widens over the life cycle.

The general shape of these profiles are a direct implication of the Ben-Porath model. Recall that in the Ben-Porath framework human capital stock is valued in the labor market and it directly maps into earnings levels. Importantly, the model is estimated to match earnings dynamics over the life-cycle, including mean levels of earnings. As such human capital levels will mirror the observed earnings gap between the two groups.

A key benefit of the Ben-Porath model is that it allows us to make inferences about agents'

Figure 9: Human Capital and Financial Assets Accumulation



time allocation between learning and earning from observed earnings profiles. Interpreting the data through the lens of Ben-Porath suggests that, early in life, households on average spend a significant fraction of their time on human capital accumulation. As agents age, diminishing returns to human capital investment and a shorter horizon to recoup these returns lead them to spend less time on human capital investment. Indeed, as retirement approaches, we see that the fraction of time allocated to human capital falls sharply for both groups. As discussed in AIN (2023), this behavior in turn has consequences for financial market investment. In particular, we expect college graduates to invest little in financial instruments early in life but rapidly increase the amount invested as they age and accumulate human capital.

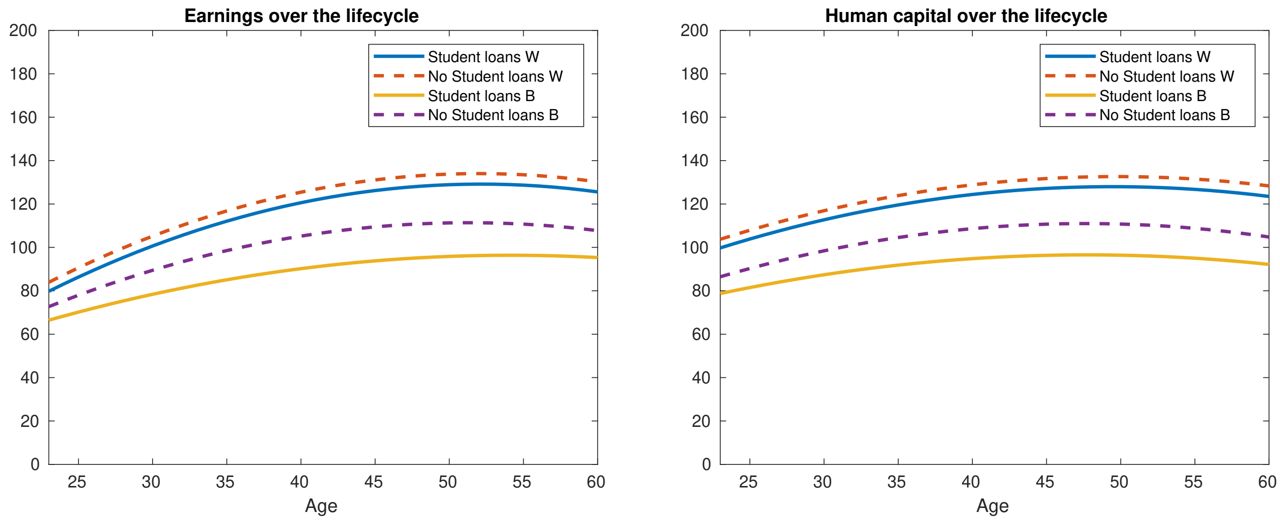
An additional feature of our model is that agents hold student loans, and the financial burden associated with these will lead to individual-specific tradeoffs between human capital and financial investment. These tradeoffs will moreover vary over the life cycle. We now turn to assessing in more detail the role played by student debt on life-cycle outcomes.

5.1.2 Student debt burden and life-cycle outcomes across groups

What role does student debt burden play in differences in earnings, human capital, and financial assets? Figure 10 displays our model's predictions for the path of human capital and earnings over the life-cycle for individuals with and without student loans across Black and White college graduates. Figure 11 displays predictions for the path of risk-free, risky, and total financial assets.

Within race, we observe that student loan holders have lower earnings over the life cycle than

Figure 10: The Role of Student Debt for Human Capital and Earnings

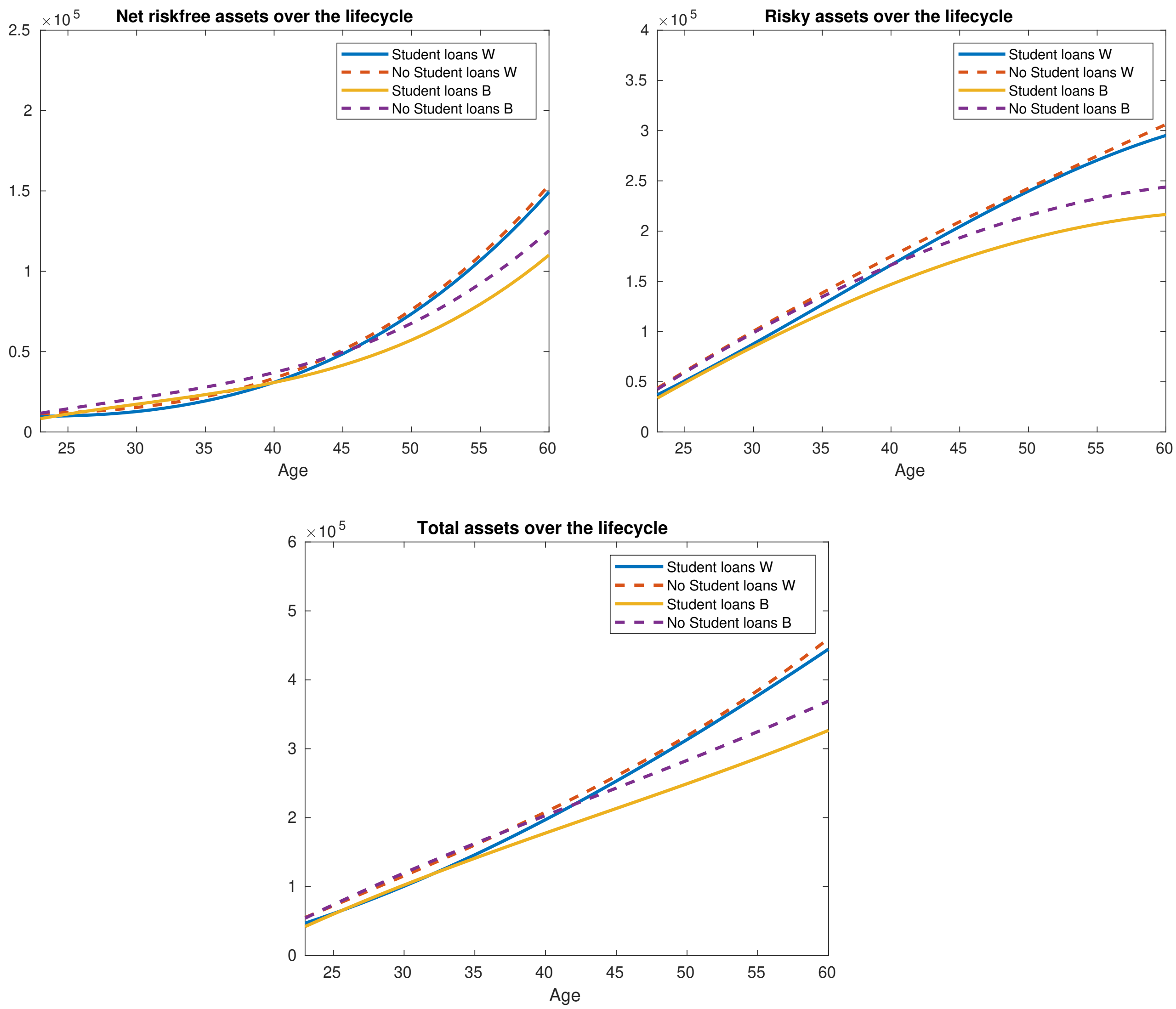


those who do not hold student debt. The gap is larger for Black individuals. Correspondingly, earnings are higher for those without student loans than those with, particularly for Black individuals. Why does student loan debt have a larger impact on Black borrwers than White borrowers, particularly given that the levels of debt across the two groups are similar? As we will demonstrate next, the interaction between initial conditions and student debt burden is key in explaining these differences.

5.2 The Role of student debt in the cross-section: interaction with initial conditions

We now turn to understanding the importance of initial characteristics and their interactions with student debt burdens for individual decisions and outcomes over the life cycle. To quantify these effects, we run several counterfactual experiments where we endow both White and Black college graduates with the same initial conditions. Specifically, we run two experiments where we change, one at a time, the distribution of initial conditions that characterize individuals in our model: in the first experiment, we change the joint distribution of unobserved characteristics estimated within the model so that Black college graduates receive the same distribution of (a,h) as White college graduates. In the second experiment, we give Black the same distribution of initial assets as their White counterparts. Our findings are illustrated in panels in Figure 9, with the left panels illustrating outcomes from the first experiment and the right panels from the second experiment. The main takeaway is that the distributions of initial learning ability and human capital are key

Figure 11: The Role of Student Debt for Financial Assets



for understanding different effects across the two race groups in both labor and financial markets, whereas the distribution of initial assets has negligible effects. In other words, if Black college graduates receive the same technology to learn and earn at the beginning of life as their White counterparts, their outcomes over the life-cycle will be no different across the two race groups. In contrast, if Black college graduates are as wealthy as White college graduates at the beginning of their working life, that does not make much difference for their decisions and outcomes.

Second, we analyze the interaction between initial conditions and student loans. Our experiments uncover several interesting implications of such interactions across race groups. As shown in the top panels of Figure 13, in the case where Black college graduates are endowed with the same technology of acquiring human capital or earn over the life-cycle, they will do so at the same rate as their White counterparts only in the case they also hold student debt. However, if individuals do not face financial burdens associated with student debt, Black college graduates accumulate even more human capital and thus have higher earnings than their White counterparts. This boos in earnings over the life-cycle in turn allow Black college graduates to accumulate even more financial assets, in particular in the case where they do not hold student debt.

5.3 Explaining the default behavior puzzle

We have conducted our quantitative analysis so far under the premises that student loans are not defaultable or they cannot be repaid under alternative repayment plans, so as to understand the effects of student debt burden in the cross-section in isolation, e.g. in an environment where borrowers do not get to appeal to any insurance mechanism embedded in the current student loan program. We now relax this assumption and study the importance played by such insurance and the importance of the interactions between student debt and initial conditions in explaining the observed default and repayment patterns across the two groups.

To be completed.

6 Conclusion

We document several important facts regarding default and repayment on student loans for Black and White borrowers. Black individuals are far more likely to have taken out student loans than their White counterparts. Conditional on borrowing, Black student borrow more that White students. Yet, Black borrowers make smaller monthly student loan payments than White borrowers because they are more likely to be enrolled in non-standard repayment plans. Finally, Black borrowers are more likely to default on their student loans than White borrowers, and the racial

Figure 12: The Role of Initial Conditions for Human Capital, Earnings, and Assets

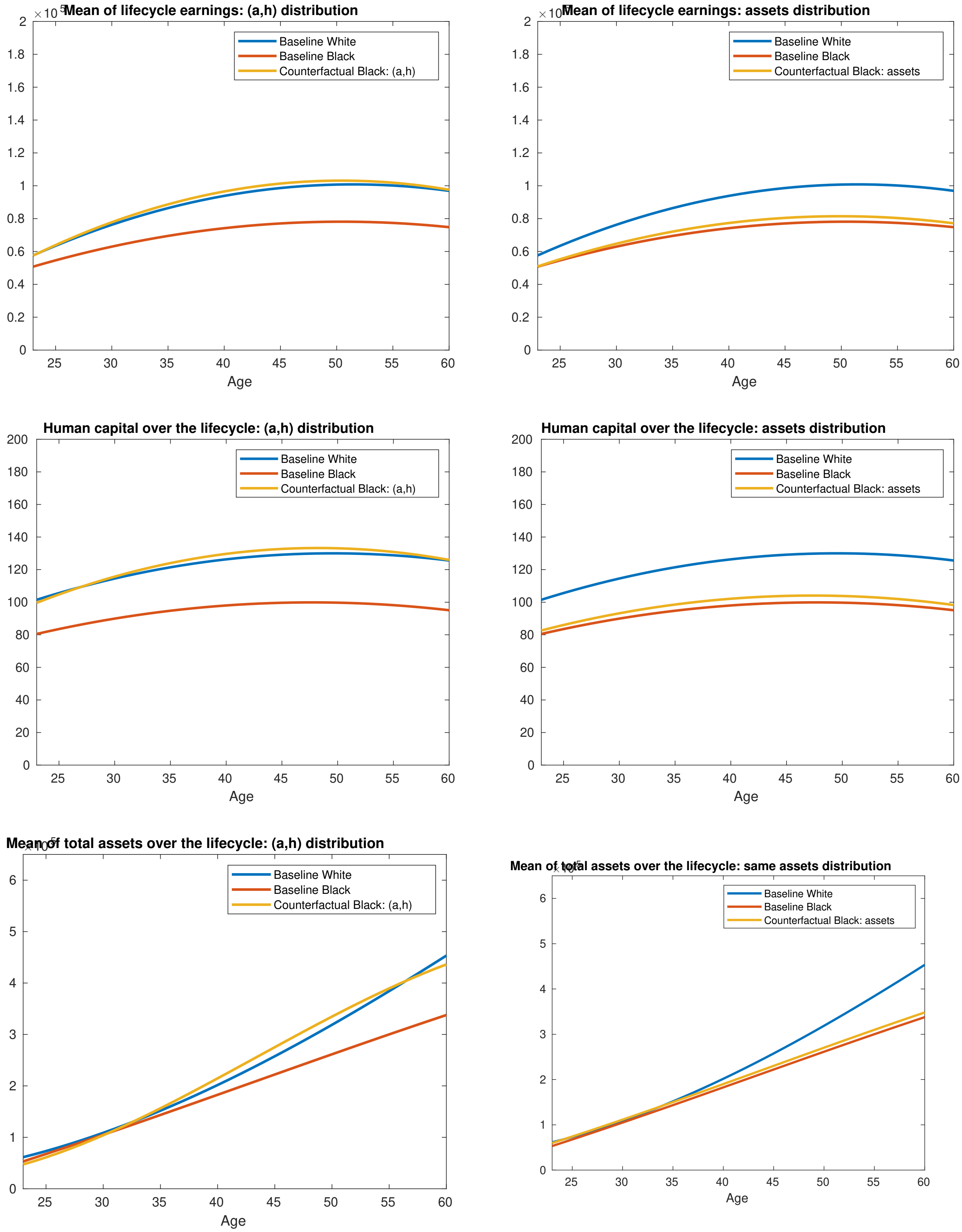
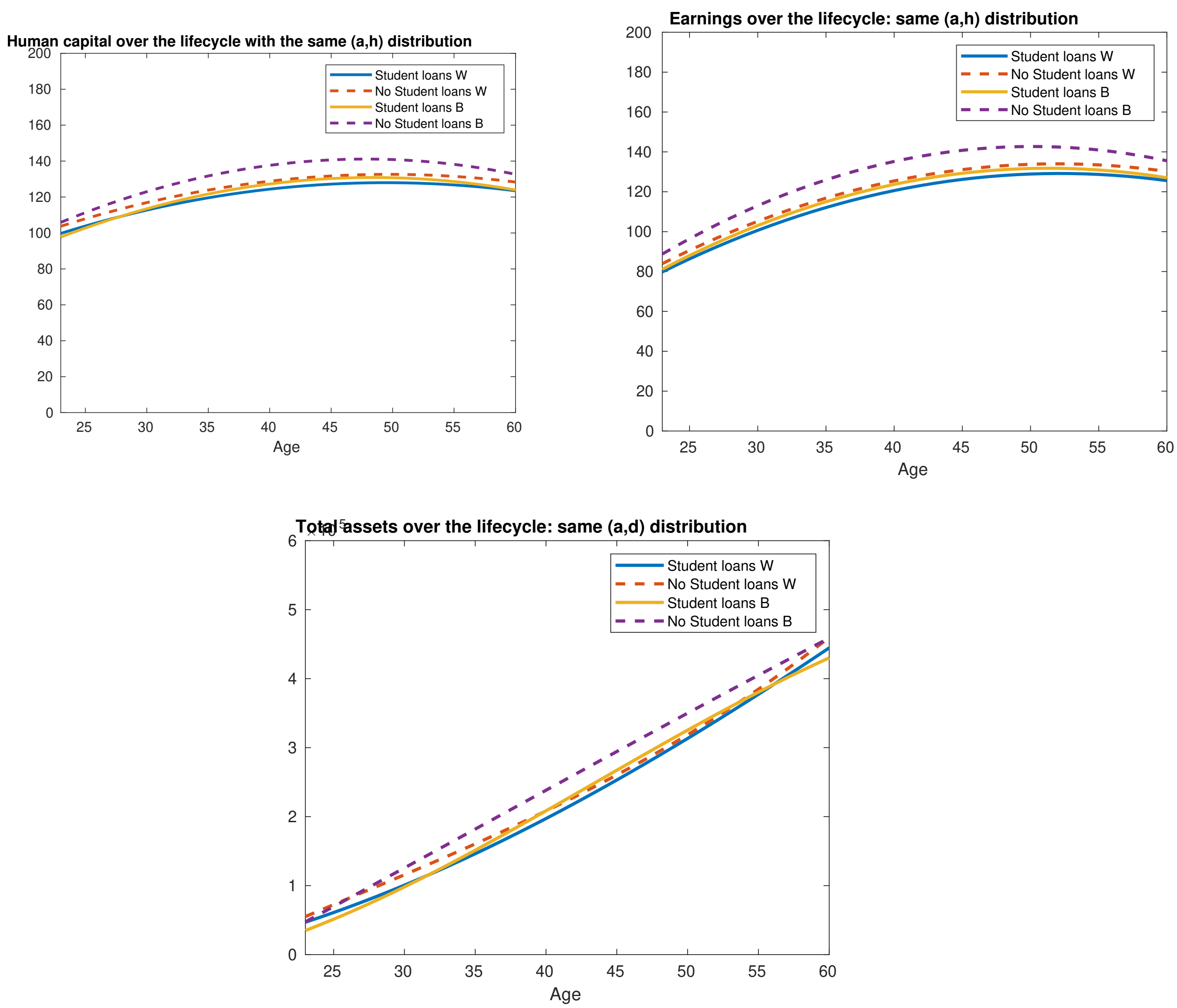


Figure 13: Interaction of Initial Conditions and Student Loans for Human Capital, Earnings, and Assets



default gap is larger for college graduates than non-graduates. Intuitively, it is likely that earnings and wealth differences play an important role in the racial differences in student loan borrowing, repayment, and default behavior. Indeed, the gap in earnings over the life cycle between Black and White individuals is evident among both college graduates and non-graduates, though it is larger for the latter. Similarly, Black graduates have less than half the net worth of White graduates, on average.

We build a life cycle consumption-savings model that captures observed heterogeneity in initial wealth, human capital risk, student loan debt and repayment choices, earnings processes, including racial wage discrimination, and unobserved heterogeneity at the time of labor market entry to quantify the degree to which each of these channels contributes to the observed gap in Black-White student loan default rates over the life cycle. We map the model to the data and use it to assess the role played by each factor in explaining the gap in default rates across groups and the implications of student debt burdens for life-cycle choices individuals make over the life-cycle. We first conduct our quantitative analysis under the premises that student loans are not defaultable or they cannot be repaid under alternative repayment plans, so as to understand the effects of student debt burden in the cross-section in isolation.

We find that for White individuals, debt relief does not substantially impact human capital accumulation paths. For Black individuals, in contrast, debt relief significantly boosts human capital accumulation and therefore earnings and wealth. We further study the importance of the interactions between student debt and initial conditions in explaining patterns across the two groups and find an important role for unobserved heterogeneity but a minimal one for initial wealth. In current work we turn to the analysis of the relative contribution of each of the relevant factors to the Black-White gap in student loan default and repayment patterns and provide insights into the differences in such drivers across education groups.

References

Athreya, Kartik, Christopher Herrington, Felicia Ionescu, and Urvi Neelakantan. 2022. "Student Loan Borrowing and Repayment Decisions: Risks and contingencies." In *The Routledge Handbook of the Economics of Education.* 458–511. Routledge.

Athreya, Kartik, Felicia Ionescu, and Urvi Neelakantan. 2023. "Stock market participation: The role of human capital." *Review of Economic Dynamics*, 47: 1–18.

Ben-Porath, Yoram. 1967. "The production of human capital and the life cycle of earnings." *Journal of Political Economy*, 75(4): 352–365.

Bertrand, Marianne, and Sendhil Mullainathan. 2004. "Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination." *American Economic Review*, 94(4): 991–1013.

Black, Dan, Amelia Haviland, Seth Sanders, and Lowell Taylor. 2006. "Why do minority men earn less? A study of wage differentials among the highly educated." *The Review of Economics and Statistics*, 88(2): 300–313.

Board of Governors of the Federal Reserve System. 2014. "Federal Reserve Statistical Release, G19, Consumer Credit." Board of Governors of the Federal Reserve System.

Browning, Martin, Pierre-André Chiappori, and Yoram Weiss. 2014. *Economics of the Family.* Cambridge University Press.

Cocco, Joao F. 2005. "Portfolio Choice in the Presence of Housing." *Review of Financial Studies*, 18(2): 535–567.

Conkling, Thomas S, and Christa Gibbs. 2019. "Borrower experiences on income-driven repayment." *Consumer Financial Protection Bureau Office of Research Reports Series.*

Davis, Steven J, Felix Kubler, and Paul Willen. 2006. "Borrowing costs and the demand for equity over the life cycle." *The Review of Economics and Statistics*, 88(2): 348–362.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, and Robert J. Warren. 2021. "Current Population Survey: Version 9.0 [dataset]." IPUMS, Minneapolis, MN. `https://cps.ipums.org/cps/` (accessed June 2022).

Fryer, Roland G, Devah Pager, and Jörg L Spenkuch. 2013. "Racial disparities in job finding and offered wages." *The Journal of Law and Economics*, 56(3): 633–689.

Goldsmith, Arthur H, Darrick Hamilton, and William Darity. 2007. "From dark to light: Skin color and wages among African-Americans." *Journal of Human Resources*, 42(4): 701–738.

Grogger, Jeffrey. 2011. "Speech patterns and racial wage inequality." *Journal of Human Resources*, 46(1): 1–25.

Hubbard, R Glenn, Jonathan Skinner, and Stephen P Zeldes. 1994. "Expanding the life-cycle model: Precautionary saving and public policy." *The American Economic Review*, 84(2): 174–179.

Huggett, Mark, Gustavo Ventura, and Amir Yaron. 2006. "Human Capital and Earnings Distribution Dynamics." *Journal of Monetary Economics*, 53(2): 265–290.

Huggett, Mark, Gustavo Ventura, and Amir Yaron. 2011. "Sources of Lifetime Inequality." *American Economic Review*, 101(7): 2923–2954.

Ionescu, Felicia. 2009. "The federal student loan program: quantitative implications for college enrollment and default rates." *Review of Economic Dynamics*, 12(1): 205–231.

McGrattan, Ellen R, and Edward C Prescott. 2000. "Is the Stock Market Overvalued?" *Federal Reserve Bank of Minneapolis Quarterly Review*, 24(4): 20–40.

Volkwein, J Fredericks, Bruce P Szelest, Alberto F Cabrera, and Michelle R Napierski-Prancl. 1998. "Factors associated with student loan default among different racial and ethnic groups." *The Journal of Higher Education*, 69(2): 206–237.

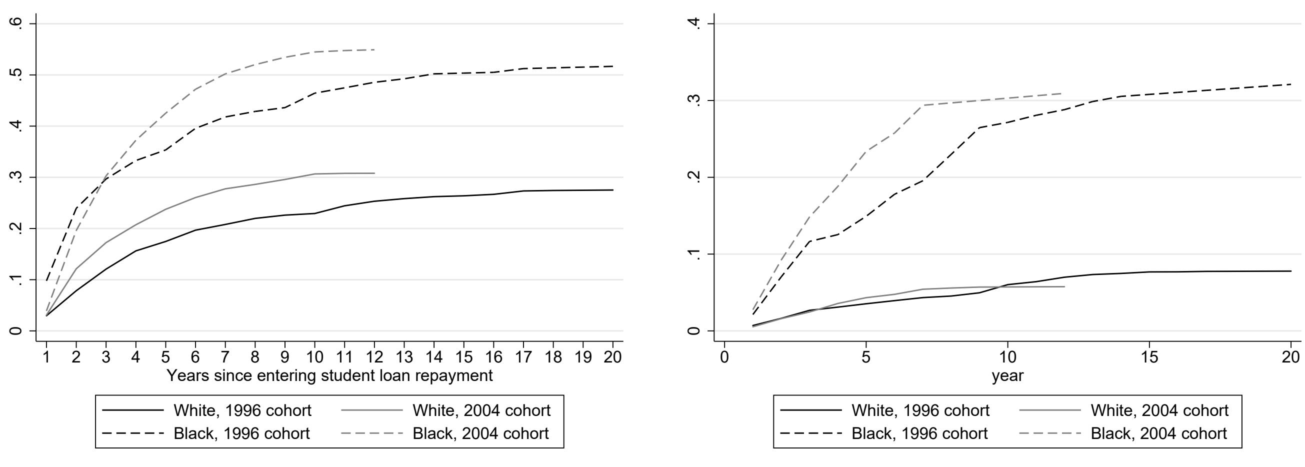
A Additional Beginning Postsecondary Students Data

In the main text our primary source for student loan data was the Beginning Postsecondary Students (BPS) 1996 survey. Here we provide additional evidence from the BPS 2004 wave for comparison. Individuals in this wave were first surveyed as first-year college students in the 2004–05 academic year, with follow-up surveys conducted in 2006 and 2009. Like the BPS 96, the BPS 04 is linked to the 2015 Federal Student Aid Supplement, which provides information about borrowing, repayment, and default outcomes for up to 12 years after the 2004 cohort started college. We limit the sample to students initially enrolled in bachelor's programs, but we note that the summary statistics are very similar if we include all college students.

Table 5: Summary Statistics from BPS 2004

	Graduates			non-completers		
	All	White	Black	All	White	Black
Share (%, 2015)	61.2	60.1	84.3	72.0	68.2	88.6
Avg cumulative loan amount ($, 2015)	18,133	17,510	24,333	19,131	18,340	23,139
Avg monthly payment ($, 2009)	251	252	215	162	166	159
Avg payment share of income (%, 2009)	11.3	10.9	9.4	8.1	7.4	12.6
Loan share of annual income (%, 2009)	55.9	55.1	67.9	49.9	47.9	55.5
Borrowers with loans paid off (%, 2015)	27.6	30.6	6.2	22.7	25.7	8.5
Amount owed / total borrowed (%, 2015)	80.9	75.3	111.3	93.7	87.6	116.1
Share ever in default (%, 2015)	7.6	5.1	24.8	36.6	29.0	59.8

Figure 14: Cumulative Student Loan Default Rates: BPS 96 and BPS 04



(a) Non-graduates

(b) Graduates

B Federal Student Loan Program Institutional Details

We describe the repayment options available to federal student loan borrowers and the rules of default.[9]

The U.S. Department of Education's federal student loan program (FSLP) is the William D. Ford Federal Direct Loan (DL) Program. Under this program, the U.S. Department of Education is the lender and sets the terms of credit, including eligibility criteria, loan limits, and interest rates, repayment plans and rules of default. Under the FSLP students start repaying their loans six months after leaving college, with or without a degree. By default, borrowers start repaying under the standard plan and have a rich menu of repayment options available, or they can choose to default.[10] We first discuss the menu of repayment options focusing on the key trade-offs that borrowers weigh in choosing a repayment plan, followed by a discussion of delinquency and default and a brief description of dischargeability and forgiveness.

Repayment options Currently, there are seven repayment plan options, of which three are "traditional" plans and four are "income-driven" . The three traditional plans are the Standard, Graduated, and Extended Repayment Plans. The Standard plan requires equal monthly payments over a 10-year timeline, while the graduated plan utilizes smaller initial monthly payments that grow over time while maintaining a 10-year horizon. The Extended plan is available only to borrowers with at least \$30,000 of debt, and it extends the repayment timeline for up to 25 years with either level or graduated monthly payments. The four income-driven repayment (IDR) plans are Pay-As-You-Earn (PAYE), Revised Pay-As-You-Earn (REPAYE), Income-Based Repayment (IBR), and Income-Contingent Repayment (ICR).[11]

As of the first quarter of 2022, almost 42% of borrowers are enrolled in the Standard repayment plan, and another 20% participate in the Graduated or Extended repayment plans. The remaining 38% of borrowers are enrolled in one of the income-driven or alternative repayment plans; however, borrowers in income-driven plans tend to have larger debt, so they collectively represent 65% of the \$1.1 trillion Direct Loan debt outstanding.[12] As noted by Conkling and Gibbs (2019), enrollment

[9]For further details on these topics and for details on the types of loans available under the current federal program, eligibility criteria, contract terms, and rules of credit, as well as a characterization of differences between federal student loans and private student loans, and recent and current repayment policy proposals, see Athreya et al. (2022).

[10]Borrowers can also file for bankruptcy, though this rarely results in the discharge of student loan debt. In addition, the Office of Federal Student Aid offers some debt relief options that can temporarily suspend payments.

[11]Note that the cohorts we study have always had access to income-based repayment plans, but not all current plans were available in all years. ICR was introduced in 1994, and the other three plans were introduced later: IBR in 2009, PAYE in 2012, and REPAYE in 2015

[12]Calculations from the Federal Student Loan Portfolio data, available at `https://studentaid.gov/`

in income-driven plans was initially low but has increased sharply in recent years.

Standard and IDR plans differ in three key ways. First, the Standard plan offers the shortest repayment timeline of 10 years. The level payments under the Standard plan pay down the principal balance fastest and therefore incur the least interest over the life of the loan. In contrast, all income-driven plans offer repayment timelines of at least 20 years, so borrowers pay more interest costs over this time. Second, the Standard plan results in the highest monthly payments because the loan is amortized into equal monthly payments resulting in full repayment at the end of 10 years. the loan in full within 10 years. While the borrower's income plays no role in the calculation of monthly payments under the traditional plans, all IDR plans calculate payments as a function of the borrower's current income. We refer to Athreya et al. (2022) for details, but in short the formulas limit payments to 10–20% of discretionary income, which is the difference between the borrower's annual income and a reference point related to the poverty threshold. Finally, the standard plan is designed to pay the loan in full at the end of the term, so it does not include principal forgiveness.[13] By contrast, IDR plans stipulate that any remaining balance will be forgiven if the loan is not paid in full at the end of the specified term.[14]

Default consequences As with any type of unsecured credit, the first day after borrowers miss a student loan payment, their loan becomes past due, or delinquent. The loan account remains delinquent until borrowers repay the past due amount or make other arrangements, such as deferment or forbearance, or change repayment plans. FSLP borrowers are considered to be in default if they have not made their scheduled student loan payments for at least 270 days. As a practical matter, delinquent student loans typically go into default.

Default on federal student loans can lead to severe financial consequences. First, the unpaid balance and accumulated interest cannot be discharged, so the entire amount becomes due immediately. To meet this obligation, a portion of the borrower's wages may be garnished, or withheld. Borrowers may also forfeit tax refunds and federal benefit payments, which may be withheld toward repayment of the defaulted loan through a process called Treasury offset. Defaulters may also be held responsible for court costs, collection fees, attorney's fees, and other costs associated with the collection process. The default is also reported to credit bureaus, which can negatively affect the borrower's ability to secure credit in the future.

data-center/student/portfolio.

[13]Exceptions to this are individuals enrolled in these plans who receive forgiveness through the Public Service Loan Forgiveness or Teacher Loan Forgiveness programs.

[14]Any amount forgiven is treated as income for tax purposes, which can be particularly problematic for borrowers whose income-driven payments are less than the amount necessary to cover accrued interest each period.