

College Loans and Post-Schooling Human Capital Investment*

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Abstract

We develop and estimate a dynamic decision model to study the potential distortion of college loan debt on workers' post-schooling trajectories and how loan repayment policies may help reduce this inefficiency. In the model, heterogeneous workers, faced with borrowing limits and the burden of college loan repayment, make dynamic decisions on consumption, savings, labor supply, and costly human capital investment. Using data from the National Longitudinal Survey of Youth, we estimate two versions of the model, one with natural borrowing limits and the other with parameterized borrowing limits. We find that workers with larger college loans are more likely to have higher efficiency in producing human capital and lower disutility of work. Accounting for these unobservables, both models suggest that college loan debt leads young workers to underinvest in their human capital and that relative to the 10-year standard repayment plan, "Pay As You Earn" plans would lead to gains in both borrowers' welfare and government revenues.

Keywords: Human Capital, Credit Constraints, Savings, College Loans

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1 Introduction

Access to college loans facilitates individuals' investment in education, especially for those with limited family resources. Therefore, it plays an important role in equalizing educational opportunities and improving welfare *ex ante*. However, after college, the burden of college loan repayment becomes a form of financial constraint that can potentially distort one's post-education human capital investment.¹ As a result, given the same educational attainment, individuals who had to borrow to attend college would start their career with a disadvantage relative to their counterparts without (significant amounts of) college debt. In this paper, we quantify such *ex post* inefficiency and inequality and examine the extent to which alternative college loan repayment policies can reduce them.

To do so, we build and estimate a dynamic model of workers' decisions on consumption, savings, labor supply (non-employed, part time, full time), and human capital investment. The model incorporates three features that are essential for our research question. First, wages grow endogenously as a result of one's costly investment that lowers one's current earnings in exchange for higher future earning potentials as in Ben-Porath (1967). Second, workers are subject to borrowing constraints, and for those who borrowed for college, the additional constraint of college loan repayment. Given the importance of borrowing constraints, which researchers do not observe, we take extra caution and use two very different specifications that are well received in the literature. In one, we build on Hai and Heckman (2017) and derive the natural borrowing limit (Aiyagari, 1994), accounting for workers' labor supply and human capital investment choices. In the other, we follow Keane and Wolpin (2001) and treat borrowing limits as a parameterized function to be estimated from the data. Third, we explicitly account for worker unobservables, which is important for evaluating any loan repayment policy: workers in our model can differ unobservably in their preferences, initial human capital, and effectiveness in producing human capital. More importantly, we allow these unobservable initial endowments to be correlated with workers' pre-market conditions, including their college loans.

Typical loan repayment policies require that loans be paid back within certain years after schooling, i.e., early in one's career. This is a stage when the return to human capital investment is high (Ben-Porath, 1967), but workers are more likely to be resource constrained. The combination of the first two features of our model implies that a rigid policy that sets a short repayment period may lead workers to underinvest in their human capital during loan-repayment years. The degree of this distortion and how fast one can catch up afterwards depend on model primitives (e.g., individuals' preferences, the severity of borrowing constraints, and the nature of human capital production technology). Ultimately, the welfare implication of alternative loan repayment policies is an empirical question.

Toward answering this question, we apply our model to data from the National Longitudinal Survey of Youth (NLSY), which allows us to follow individuals for periods both before and after their college

¹The burden of college debts can have other types of distortions beyond that on human capital investment. For example, some research shows that debt loads discourage students from pursuing low-paying service careers, such as working as teachers or for non-profit organizations (e.g., National Student Loan Survey '97, Nellie Mae, October 1997; Debt Burden: The Next Generation, Final Report, U.S. Department of Education, September 1993).

loans were paid back under the standard repayment plan. We estimate both versions of our model via indirect inference and design auxiliary models to highlight data patterns that are important for model identification, including how individuals’ wage and asset trajectories (both overall and in loan repayment years) correlate with their initial assets and college loans. Estimates from both models suggest that, between two otherwise similar workers, the one with larger college loans is more likely to have higher efficiency in producing human capital and lower disutility of work. Young individuals are estimated to face tighter borrowing limits in the model with parameterized borrowing limits (PBL) than they are in the model with natural borrowing limits (NBL).

Using our estimated models, both of which replicate data patterns well, we conduct two sets of counterfactual policy simulations. In the first, college loans are (unexpectedly) entirely forgiven upon workers’ entry into the labor market. This simulation serves two purposes: First, it quantifies the *ex post* welfare loss from the burden of college loan repayment. Second, it helps to understand the effect of similar policies that may be implemented in rare situations.² Compared to their baseline decisions, debt-relieved workers invest more in human capital and earn less in early years of their careers in exchange for higher lifetime earnings; these behavioral responses are larger under PBL than they are under NBL. On average, workers with college loans would be better off by \$1,086 worth of annual consumption under NBL and by \$1,379 worth of annual consumption under PBL. Accounting for both the loss in loan repayment and the gain in income tax revenues (as workers now have higher lifetime earnings), the government would lose a total of \$10,224 (\$9,094) per borrower in present value terms under NBL (PBL), which is, however, easily outweighed by borrowers’ welfare gains.

In a second set of counterfactual experiments, we study the effect of a less extreme class of repayment policies known as “Pay As You Earn” (PAYE) plans. Under a PAYE plan, individuals pay the minimum of a fraction α of their discretionary income and a fixed amount up to N years, after which the remaining college debt is forgiven. Various PAYE plans differ from one another mainly in policy parameters α and N ; we study two examples. The first policy (PAYE₁) resembles the current PAYE plan with $\alpha = 10\%$ and $N = 20$. The second policy (PAYE₂) resembles the one proposed by the Trump administration with $\alpha = 12.5\%$ and $N = 15$. In both cases, we allow a worker to choose between the standard 10-year plan and the corresponding PAYE plan. Relative to total loan forgiveness, which removes any distortion college loan debt may have on workers’ decisions, we find that both PAYE policies lead workers to *overinvest* in their human capital. This is because PAYE policies operate essentially as income taxes, thereby creating incentives for borrowers to earn less during loan-repayment periods. Borrowers do so by overinvesting in their human capital, rather than reducing their working hours (policy effects on hours are negligible). Despite the earning disincentive they create, both PAYE policies not only improve individual borrowers’ welfare but also increase government revenues.³ Relative to PAYE₁; PAYE₂ leads to larger gains in borrowers’ welfare but smaller gains in government revenues.

²For example, by July 2021, the Biden administration had canceled \$1.5 billion in student loan debt as a response to the COVID-19 pandemic.

³Borrowers’ welfare gains under either PAYE are smaller than they are under total debt forgiveness.

The rest of this paper is organized as follows. Section 2 reviews the related literature. Section 3 takes a first glance at the data, which motivates our model presented in Section 4. Section 5 describes the data in detail. Section 6 describes our estimation method, followed by estimation results in Section 7. Section 8 conducts counterfactual policy experiments. Section 9 concludes the paper. Additional details and tables are in the appendices.

2 Related Literature

There has been an extensive body of work on the effect of credit constraints on individuals' educational choices (e.g., Carroll, 1997, Cameron and Heckman, 1998, Keane and Wolpin, 2001, Carneiro and Heckman, 2002, Carroll et al., 2003, Cameron and Taber, 2004, Belley and Lochner, 2007, Stinebrickner et al., 2008, Johnson, 2013, and Lochner and Monge-Naranjo, 2016). Our paper complements this literature by examining the effect of post-education credit constraints on one's post-education decisions, especially for those burdened with college loan repayment.

The literature has used different approaches to modeling credit constraints. Some studies (e.g., Keane and Wolpin, 2001 and Johnson, 2013) treat borrowing limits as a function of age and human capital with free parameters to be estimated from the data. Other studies model borrowing constraints in a more disciplined way.⁴ For example, Lochner and Monge-Naranjo (2011) study the interaction between borrowing constraints and investment in human capital during schooling years, where borrowing constraints are derived from government student loan programs and private lending under limited commitment. Hai and Heckman (2017) estimate a dynamic model of schooling, labor supply, work experience and savings with uninsured human capital risks and borrowing constraints. They model credit constraints as model-determined limits derived from an analysis of private lending with a natural limit (Aiyagari, 1994) combined with access to government student loan programs; theirs is the first analysis that incorporates the natural borrowing limit in such a rich framework. They use their model to investigate the role of cognitive ability, noncognitive ability, and family background in explaining inequality in education, earnings, and consumption. They find substantial evidence of life cycle credit constraints that affect human capital accumulation and inequality. Moreover, borrowing limits vary with age and are lower for individuals with lower human capital and higher psychic costs of working. Comparing their model with one where borrowing limits are fixed to sample means stratified by education level (Abbott et al., 2019), they find that the latter overpredicts the effect of tuition policies.⁵ We model borrowing constraints in two specifications, building on Hai and Heckman (2017) and Keane and Wolpin (2001), respectively.

Our paper also builds on the broad literature on the relationship between human capital investment and life-cycle wage growth, which follows the Ben-Porath (1967) model. Earlier work that explicitly estimates the Ben-Porath model includes Heckman (1975, 1976), Haley (1976), Rosen (1976), and

⁴See Hai and Heckman (2017) for a comprehensive review of the literature on this issue.

⁵With a similar model-determined borrowing limit, Hai and Heckman (2019) estimate a dynamic model of schooling, health behavior, and wealth in order to quantify causal relationships between education and health.

Heckman et al. (1998a,b). For example, Heckman (1976) extends Ben-Porath (1967) and presents more general human capital models in which each individual makes decisions on labor supply, investment and consumption. More recently, Fan et al. (2015) focus on the later part of one’s career and estimate a Ben-Porath model with endogenous retirement.

Also adopting a Ben-Porath framework, Ionescu (2009, 2011) calibrates life cycle models of college enrollment, college loan take-up, post-education human capital accumulation, earnings and loan repayment. One major difference between her two papers is the modeling of borrowing limits. In Ionescu (2009), a worker is not allowed to borrow; in Ionescu (2011), a worker faces no borrowing limit unless he defaults on his college loan debt. Her papers highlight how bankruptcy and loan consolidation policies may affect the composition of college enrollees and loan default rates. Our paper well complements hers. We are mostly interested in how college loan debt may affect a worker’s post-education trajectories. To this end, we abstract from pre-market decisions; instead, in a more focused model, we study how the burden of loan repayment interacts with borrowing limits in affecting workers’ decisions, accounting for their unobservable heterogeneity. In modeling borrowing limits, we take two different and less extreme approaches than those in her papers. In addition, utilizing micro-level panel data, we take a different empirical approach and estimate all of the key structural parameters jointly within the model.

3 A Glance at the Data

As we describe in detail in Section 5, our data consist of a sample of college-educated white males from the National Longitudinal Survey of Youth. To motivate some of our modeling choices, we provide a first glance at our data and show profiles of wage growth for college loan borrowers versus non-borrowers. Specifically, we calculate each individual’s annual wage growth on full-time jobs over time and report the average among individuals in each (education, loan status) group. The left panel of Figure 1 shows that among those with some college education (but without a bachelor’s degree), college loan borrowers have lower wage growth throughout the first ten years of their career compared to non-borrowers. The right panel shows that relative to those without college loans, college graduates with loans have lower wage growth in the first few years of their career but higher wage growth later on.

Without excluding other explanations, patterns shown in Figure 1 are consistent with the hypothesis that the burden of repaying college loan debt may put workers at a disadvantage and lead them to underinvestment in their human capital at the beginning of their career. These patterns motivate us to model wage growth as an endogenous result from costly human capital investment as in Ben-Porath (1967). However, cross-group comparison may lead to biased views as it is confounded by unobserved differences between borrowers and non-borrowers. To obtain a solid understanding of patterns such as those in Figure 1 and to conduct counterfactual policy simulations, we resort to the structural model we describe next.

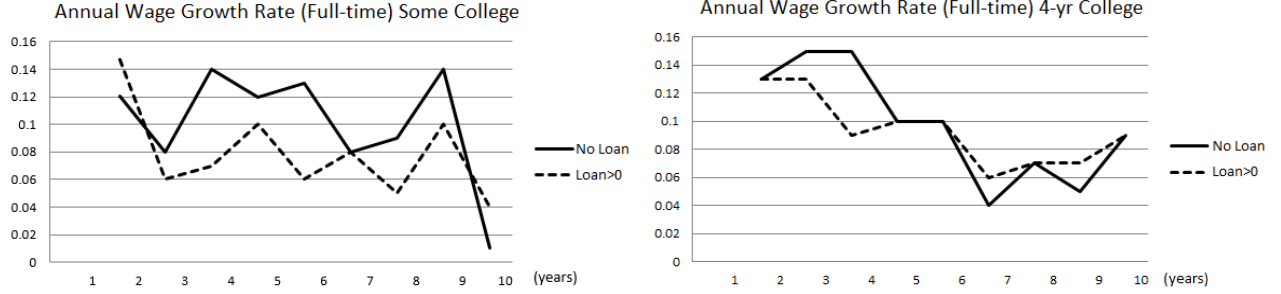


Figure 1: Wage Growth for Workers with and without Loans by Education

4 Model

4.1 Primitives

We model an individual’s post-education decisions in a dynamic framework. In each period $t = 1$ until Age , one makes decisions on labor supply $h_t \in \{0, 1, 2\}$ (non-employment, part-time employment, full-time employment), human capital investment $i_t \in [0, 1]$, and savings/borrowing subject to a borrowing constraint.

Initial Endowment An individual is endowed with a vector of observable characteristics X , a type $\theta \in \{1, 2\}$, and an initial human capital level k_0 . The vector X consists of one’s education $e \in \{1, 2\}$ (some college, four-year college graduate), college loan amount l_0 , initial (non-college loan) asset level a_0 , Armed Forces Qualification Test (AFQT) score, parental education, and age at which one leaves school age_0 . One’s type and initial human capital are unobservable to the researcher and are correlated with X such that

$$\Pr(\theta = 2 | X) = \frac{\exp(X^\theta)}{1 + \exp(X^\theta)} \text{ and } k_0 = K_0(X, \theta): \quad (1)$$

That is, the distribution of types varies across individuals with different X , governed by a logistic function with parameters β ; the initial human capital level k_0 differs by both X and type θ ; governed by the function $K_0(\cdot)$:

We focus on post-education decisions while taking one’s education (e) and college loan (l_0) as pre-determined. To capture the idea that one’s pre-market conditions and post-education decisions may be driven by common unobservables, we introduce unobserved type and initial human capital, both of which are allowed to be correlated with $(e, l_0) \in X$ as in (1): The two unobservables serve different roles in the model: k_0 determines one’s initial earnings potential, while types differ in their preferences, initial human capital, and efficiency in producing human capital.

Earnings and Human Capital Production A worker can use a fraction of his human capital for skill-enhancing human capital investment and rent the rest to the labor market. Human capital investment therefore involves an opportunity cost in the form of foregone earnings (Ben-Porath, 1967).

In particular, for a worker with working status $h_t \in \{0, 1, 2\}$ who uses a fraction $i_t \in [0, 1]$ of his human capital (k_t) for skill investment and hence rents $k_t(1 - i_t)$ amount of human capital to the labor market, his earnings in period t are given by

$$y_t = p_{h_t} k_t (1 - i_t) e^{\varepsilon_t}; \quad (2)$$

where $p_0 = 0$ and hence $y_t = 0$ if one does not work; p_1 and p_2 are rental rates of human capital on part-time and full-time jobs respectively; ε_t is an i.i.d. wage shock.

The evolution of one's human capital is governed by

$$k_{t+1} = (1 - \delta) k_t + \alpha_{h_t} A i_t^{1-\beta} k_t^\beta; \quad (3)$$

where δ is the human capital depreciation rate. The overall productivity in human capital production varies with one's work status h ; as governed by the work-status-specific parameter α_h ;⁶ it may also vary across types, as governed by the type-specific parameter A . Finally, $\beta, \gamma \in (0, 1)$ govern the importance of investment and that of human capital stock, respectively.⁷

Preferences One cares about consumption and leisure, with the contemporaneous utility given by

$$u(c; h; \eta) + \eta = \frac{c^{1-\sigma}}{(1-\sigma)} - \eta + \eta'; \quad (4)$$

where σ is a scale parameter, $\frac{1}{\sigma}$ is the elasticity of intertemporal substitution, $\eta - \eta'$ is the disutility from working part (full) time for a type- η individual (η_0 is normalized to 0). Finally, η is an i.i.d. work-status-specific preference shock drawn from the type-I extreme value distribution.

College Loan Repayment In the baseline model, we assume that one pays back his college loans according to the standard plan as described in Smole (2013). This plan was used by more than 90% of college loan borrowers in the cohorts covered by our data (Scherschel, 1998). Under the standard plan, one pays back his college loan l_0 within the first 10 years after leaving college, with the annual payment given by

$$\bar{l}(l_0; t) = \begin{cases} \frac{l_0}{10} \frac{(1+r^c)^9}{(1+r^c)^t - 1} & \text{if } t \leq 10; \\ 0 & \text{if } t > 10; \end{cases} \quad (5)$$

where r^c is the interest rate on college loan debt. Given this payment plan, the evolution of one's college loan debt is given by

$$l_{t+1} = l_t + \bar{l}(l_0; t) - (1 + r^c) l_t;$$

⁶We assume that human capital can grow only when one works, i.e., $\alpha_{00} = 0$; we normalize $\alpha_{02} = 1$ for full-time jobs and estimate part-time α_{01} as a free parameter.

⁷Similar functional forms have been used to specify human capital production functions in the literature, e.g., Uzawa (1965), Ben-Porath (1967), Rosen (1976), Ortigueira and Santos (1997) and Heckman et al. (1998a).

Borrowing Limits Because borrowing limits are a very important yet unobserved factor underlying individuals' choices, we take extra caution in our modeling choice and use two different specifications that are well received in the literature. In the first specification, we follow Hai and Heckman (2017) and assume that a worker faces an endogenous natural borrowing limit (NBL) such that

$$a_{t+1} - l_{t+1} - \underline{b}_{t+1} = B_t(l_0; k_{t+1}; \cdot); \quad (\text{NBL})$$

where $B_t(\cdot)$ is the maximum amount an individual can repay with certainty. As detailed in Appendix A4, our derivation of the natural borrowing limit $B_t(\cdot)$ extends Hai and Heckman (2017) to account for one's human capital investment decision $i_t \in [0; 1]$ in addition to one's labor supply decision $h_t \in [0; 1; 2g]$.

In the second specification, we follow Keane and Wolpin (2001) and model borrowing limits as a parametric function of age and human capital. Under the parameterized borrowing limits (PBL), one faces the following constraint

$$a_{t+1} - l_{t+1} - \underline{b}_{t+1} = \exp(\alpha + \beta \text{age}_t + \gamma k_t); \quad (\text{PBL})$$

Notice that both specifications relate workers' borrowing limits to their earning potentials. This relationship naturally arises in NBL by definition; it arises in the second specification via the inclusion of human capital in the PBL function.⁸

State Variables The vector of state variables (Ω_t) at time t consists of the following:

- a) one's observed and unobserved characteristics that are constant over time (X and θ);
- b) $\text{age}_t = \text{age}_0 + t$;
- c) the endogenously evolving asset and human capital stock (a_t and k_t); and
- d) transitory shocks to preferences and earnings (ϵ_t and η_t).

The evolution of Ω_{t+1} depends on Ω_t and one's decisions at time t : We will suppress this dependence in our notation.

4.2 Individuals' Problem

In each period $t < \text{Age} = \text{age}_0$; given Ω_t , an individual chooses his asset level for the next period a_{t+1} ; current consumption c_t ; work status h_t , and human capital investment i_t according to the following

⁸Hai and Heckman (2017) points out that for policy evaluations, it is important to account for the fact that workers' borrowing limits may vary with their human capital levels.

problem:

$$\begin{aligned}
V_t(\Omega_t) &= \max_{a_{t+1}; c_t; h_t} \left[u(c_t; h_t) + \beta E V_{t+1}(\Omega_{t+1}) \right] & (6) \\
s.t.: c_t &= \max_{y_t} \left[y_t - (y_t) + a_t (1 + r^l) I(a_t > 0) + (1 + r^b) I(a_t < 0) - \bar{l}(l_0; t) - a_{t+1} \right] \geq \underline{c} \\
k_{t+1} &= (1 - \delta) k_t + \theta h_t A i_t^\alpha k_t^{1-\alpha}; \\
y_t &= \rho h_t k_t (1 - i_t) e^{-\delta t}; \\
a_{t+1} &= l_{t+1} - \underline{b}_{t+1};
\end{aligned}$$

where β is the discount factor and the expectation is taken over the next period's shocks to preferences and earnings (ϵ_{t+1} and ϵ_{t+1}). An individual faces four constraints: the budget constraint, the human capital production function, the earnings function, and the borrowing constraint, given by NBL (PBL) in the first (second) model specification. In particular, one's resource consists of one's after-tax earnings $y_t - (y_t)$ and asset a_t plus interest (r^l and r^b are the interest rates for lending and borrowing, respectively). This resource is to be divided between loan repayment $\bar{l}(l_0; t)$ (given by (5) in the baseline), next period's asset level a_{t+1} , and current consumption c_t . However, with the presence of government means-tested transfers, c_t is bounded from below by the consumption floor \underline{c} .⁹ Notably, since wages are subject to shocks, a heavier burden of loan repayment and/or a tighter borrowing limit would strengthen individuals' savings incentives to safeguard against bad wage shocks.

To close the model, we specify the terminal value at time $T = Age - age_0$ as a type-dependent function of one's asset a_T and human capital k_T ; given by

$$V_T(\Omega_T) = V(a_T; k_T);$$

The model does not have a closed-form solution. To save on computation, we set $Age = 45$. We solve the model by simulation using backward induction, where we employ discretization of continuous choice variables and value function interpolation (see the online appendix for details).

5 Data

The National Longitudinal Survey of Youth (NLSY79) provides information about individuals' characteristics and family backgrounds, college loan amounts, and the trajectories of work status, wages, and assets. We focus on white males from the main sample who have ever attended college (1,711 individuals) but exclude those who attended graduate schools (335 individuals). Among these, we drop observations missing information on AFQT, school-leaving age and/or parental education (165 individuals). We focus on those who finished education (including dropping out of college) between

⁹When an individual is at both the consumption floor \underline{c} and the borrowing limit \underline{b}_{t+1} , there may be multiple levels of i_t supporting this scenario. In that case, we assume the lowest i_t among the ones that support $\underline{c}, \underline{b}_{t+1}$ to avoid individuals heavily engaging in investment while free-riding on \underline{c} , which is presumably implausible. However, we have also re-estimated the model without this assumption; our estimates and counterfactuals are robust.

ages 17 and 35 and thereby exclude 138 individuals. The final sample consists of 1,073 individuals, of whom we follow until age 45 (terminal age in our model). We drop 501 individual-year observations of net assets or hourly wages that are extreme outliers, leaving a total of 12,898 individual-year wage observations and 9,835 individual-year asset observations.¹⁰ In the following, we provide empirical definitions of our model variables. Throughout the paper, all dollar values are in 2012 USD.

Education: We focus on those who have ever attended college but not graduate school. One is defined as a college graduate if he has a four-year college degree, all the others are categorized into the some-college group.

College Loans: l_0 refers to the total amount borrowed for one’s college education. If one attended more than one college, l_0 is the sum of loans taken for all colleges he attended.

Assets: For $t \geq 1$; net assets ($a_t - l_t$) are calculated as the sum of the following six items (i) housing, (ii) savings and checking accounts, money market funds, retirement accounts, stocks, bonds, (iii) farm operation, business or professional practice, other real estate, (iv) vehicles (v) other items worth individually more than \$500, and (vi) other debts over \$500. Although initial loan l_0 is recorded, the asset survey did not explicitly ask the amount of unpaid college loans over time. As shown in Keane and Wolpin (2001), unpaid college loans are included in item (vi).

One’s initial asset (a_0) refers to his assets right after he completed schooling. We only observe a_0 for 504 individuals. Using these individuals, we impute the initial asset for the rest of the sample using their characteristics.¹¹

Period- T Natural Borrowing Limit: $B_T(\cdot)$ is set at the third percentile of the asset distribution among individuals aged 43 to 47 in our sample, which is \$8,531.¹²

Work Status: The empirical definition of work status uses information on weekly work hours and the number of weeks worked within a year. An individual is said to work full time ($40hr=wk$) in year t if the average number of weekly hours is 30 or more and the number of weeks worked is 40 or more in t . Among the others, one is said to work part time ($20hr=wk$) in year t if his average weekly hours in t are between 10 and 30 and is considered to be non-employed in year t if his average weekly hours in t are below 10.

¹⁰Outlier individual-year observations are those with asset levels beyond the top/bottom 3 percent, or wages out of the top/bottom 1 percent.

¹¹NLSY79 started collecting asset data in 1985, but 47% of our sample entered the labor market before 1984. Using the 504 individuals with information on (a_0), we regress a_0 on education, loan group, education² loan group, l_0 , l_0^2 , family income (at age 16-17), family income² loan group, parents’ education, the age entering labor market (age_0) and AFQT score, where loan group refers to whether or not l_0 is above the mean within one’s education group. We then use the estimated regression coefficients to impute a_0 for the rest of the sample.

¹²We have estimated the model using the 1st percentile and the 5th percentile of the asset distribution as B_T ; our counterfactual policy implications are similar. Details are available upon request.

Wages: We measure wages using the hourly rate of pay variable in NLSY. If one worked on more than one job during a week, we use the hourly wage of the main job. As in Johnson (2013), we use the cross-week average of this hourly wage measure as one’s hourly wage in a given year. This measure is used as an outcome variable in our auxiliary models. In the structural model, we focus on annual earnings y_t : The model’s counterpart of hourly wage is y_t divided by work-status-specific annual hours (40–52 for full time, 20–52 for part time).

Remark 1 *NLSY79 and NLSY97 are two natural data sets for the empirical application of our model. We choose NLSY79 as our data source mainly for two reasons. First, we focus on the interaction between college loan repayment and post-education human capital investment; NLSY79, being a longer panel than NLSY97, allows us to follow an individual for more years, and in particular, before and after one paid back his college loans. Second, neither NLSY79 nor NLSY97 contains information on one’s repayment plan choices. For NLSY79 cohorts, although not ideal, it is relatively reasonable to assume that individuals follow the standard 10-year plan because options were limited and the standard plan was chosen by over 90% of borrowers in those years (Scherschel, 1998). In contrast, later cohorts were given more repayment options and borrowers’ choices became more diversified based on aggregate statistics. As such, it is critical to observe individual repayment plan choices in order to properly study the NLSY97 cohorts.*

5.1 Summary Statistics

Panel A of Table 1 summarizes individual characteristics by education (some college vs. college graduate) and initial college loan status (without vs. with loans). Of the 631 individuals with some college education, only 142 had college loans (\$7,900 on average). Of the 442 college graduates, 253 had college loans (\$14,400 on average). Compared to those without loans in the same education group, those with college loans had, on average, higher AFQT scores, better-educated parents, and lower initial assets, and they also tended to be older when they entered the labor market.

Panel B summarizes outcomes in early and later stages of one’s career. The first four rows in Panel B show work status. Within each of the four groups, individuals work more when they are between 40 and 45 years old than they do in the first 5 years of their career. College graduates work more than those with some college education in both early and later periods. Within the same education group, working hours are similar between loan borrowers and non-borrowers. Since the majority of individuals work full time, the next two rows report hourly wages on full-time jobs. As expected, wages grow over time for all groups. Within the some-college group, relative to non-borrowers, borrowers have slightly lower wage rates in both early and later periods. Among college graduates, borrowers have higher wage rates in the first 5 years and slightly lower wage rates in their forties than their non-borrower counterparts. The last row shows that at age 45, borrowers with some college education have lower assets than their non-borrower counterpart, as is the case for initial assets (Panel A). In contrast, at age 45, borrowers with college degrees have higher assets than non-borrowers, despite that they started with lower initial assets.

Table 1: Summary Statistics

	Some College		College Graduates	
	No Loan	Loan > 0	No Loan	Loan > 0
<u>Panel A: Characteristics</u>				
College Loan (\$1,000)	0	7.9 (7.9)	0	14.4 (12.0)
AFQT	48.8 (24.9)	60.5 (23.6)	71.4 (19.5)	76.3 (18.4)
Parent Education = High School	48.1%	51.4%	28.0%	34.4%
Parent Education > High School	33.5%	37.3%	63.5%	60.5%
Initial Net Asset (\$1,000)	22.4 (35.6)	14.1 (22.6)	32.5 (41.4)	20.9 (42.7)
Age Leaving School	22.9 (5.2)	25.0 (4.7)	24.6 (4.0)	25.5 (4.2)
<u>Panel B: Outcomes</u>				
% Full-time (1 t 5)	74.0	74.0	85.5	85.2
% Part-time (1 t 5)	15.0	14.2	8.5	10.6
% Full-time (Age 40-45)	84.8	86.7	91.6	91.9
% Part-time (Age 40-45)	8.2	6.4	3.7	4.3
Full-time Wage (\$) (1 t 5)	18.9 (8.8)	18.0 (8.7)	21.7 (9.4)	23.4 (9.5)
Full-time Wage (\$) (Age 40-45)	27.9 (15.7)	26.5 (13.6)	43.9 (28.3)	43.1 (24.1)
Net Asset Age 45 (\$1,000)	258.2 (275.8)	178.7 (233.1)	399.3 (254.5)	410.4 (307.0)
Total Obs.	489	142	189	253

Standard deviations are reported in parentheses. All dollar values are measured in 2012 USD.

6 Estimation

6.1 Preset Parameters

We preset a subset of model parameters (reported in Table 2) that are not the focus of this paper. Some of these parameters are very challenging to identify (the risk aversion coefficient and the consumption floor); the rest are interest rates and the tax schedule. We set them as follows:

- i) We set the risk-averse coefficient $\gamma = 2.0$ as in, for example, Lochner and Monge-Naranjo (2011), Johnson (2013), Hai and Heckman (2017) and Hai and Heckman (2019).
- ii) Following Hai and Heckman (2017), we calculate the consumption floor (\underline{c}) as the average amount of means-tested transfers (including food stamps, AFDC and WIC) among recipients in NLSY79.¹³
- iii) We set the interest rate for college loans (r^c) at the average real interest rate of Stafford loans between 2001 and 2005, the interest rate for borrowing r^b at the average real prime rate between 2001 and 2007 plus a 2% risk premium, and the interest rate for savings (r^a) at the average real interest rate on one-year U.S. government bonds from 2001 to 2007.

¹³Hai and Heckman (2017) use NLSY97 and we use NLSY79, but our \underline{c} is similar to theirs, which is reported as \$2,800 in 2004 USD (\$3,403 in 2012 USD).

iv) For the income tax schedule (y_t) , we adopt the functional form and parameter values from Gouveia and Strauss (1994) and Imrohroglu and Kitao (2012) such that

$$(y_t) = \tau_0 y_t (y_t^{-1+\tau_2})^{-1-\tau_1};$$

where τ_0 measures the average tax rate, τ_1 governs tax progressiveness, and τ_2 is a scale parameter.¹⁴

Table 2: Preset Parameters

Discount rate	β	0.95
Risk averse coefficient	ρ	2.00
Interest rate for college loans, borrowing and savings	\bar{r}^c, r^b, r^a	f 2.2%, 5.9%, 0.9% g
Consumption floor	\underline{c}	\$3,317
Income taxation	$f\lambda_0, \lambda_1, \lambda_2$	f 0.258, 0.726, 6.158 g

6.2 Structural Estimation

We use indirect inference to estimate structural parameters (Θ) that govern 1) preferences, 2) the distribution of types and initial human capital levels, 3) the human capital production function, 4) human capital rental prices and the wage distribution, and 5) the terminal value function. For the model with parameterized borrowing limits (PBL), Θ includes additional parameters governing the borrowing limit function. The estimation consists of two steps. The first step computes from the data a set of “auxiliary models” that summarize the patterns in the data to be targeted for the structural estimation. The second step repeatedly simulates data with the structural model, computes corresponding auxiliary models using the simulated data, and searches for the model parameters to match the auxiliary models from the data. Formally, letting $\bar{\cdot}$ denote our chosen set of auxiliary model parameters computed from data and ${}^b(\Theta)$ denote the corresponding auxiliary model parameters obtained from model-simulated data (parameterized by a particular vector Θ), the structural parameter estimator is given by

$$\hat{\Theta} = \operatorname{argmin}_{\Theta} [{}^b(\Theta) - \bar{\cdot}]^{\ell} W [{}^b(\Theta) - \bar{\cdot}];$$

where W is a diagonal weighting matrix.

6.2.1 Identification

Our model extends the classical Ben-Porath framework to include two financial constraints – the borrowing constraint and the burden of college loan repayment. Similar to other dynamic models with unobserved types, the identification relies on the panel data structure, combined with exclusion

¹⁴This functional form is proposed by Gouveia and Strauss (1994) and has been employed in many quantitative studies including Castaneda et al. (2003), Conesa and Krueger (2006), and Conesa et al. (2009).

restrictions and functional form assumptions. In the following, we provide the intuition for our model identification, which guides our choice of auxiliary models. In the online appendix, we show the sensitivity of the objective function value with respect to each of the parameters of the model, as in Adda et al. (2017).

Given that one’s type is time invariant, the most important source of identification is the panel data structure, which allows us to observe the same individual’s dynamic decisions over time. The burden of college loan repayment, which follows a known formula, serves as another importance source of identification. First, it helps us to separate the true effect of college loan burden from the correlation between college loan and one’s unobserved type. Specifically, although one’s type is permanent, the burden of loan repayment lasts only for the first 10 years of one’s career under the standard repayment plan. Therefore, within-individual comparison across different stages of one’s career (e.g., first ten years versus the later years) gives us information about the effect of the burden of loan repayment. In contrast, the comparison across two otherwise equivalent individuals who have different loan amounts combines both the effect of the burden of loan repayment and the difference in their types.

Second, the burden of college loan repayment can also help us identify the human capital depreciation rate. The classical argument used to identify this parameter in Ben-Porath models is that workers will stop investing in their human capital near the end of their working years, the wage profile of whom identifies the depreciation rate of human capital (e.g., Heckman et al., 1998a). We focus on one’s earlier career and hence cannot use the same argument. However, due to the burden of loan repayment, individuals with little initial assets and large college debts are almost unable to invest in their human capital.¹⁵ The depreciation rate of human capital, which is assumed to be common among all agents, is thus identified using a similar non-investment argument, although the non-investment in our case arises from loan repayment burden rather than age.

We also impose an exclusion restriction and assume that conditional on all the other individual and family background variables (including college loan, AFQT score, own education, parental education, and the school-leaving age), one’s initial (non-college-loan) asset is not correlated with his type or initial human capital.¹⁶ For individuals with large initial assets, financial constraints would not distort their decisions and thus the model boils down to a classical Ben-Porath model without financial constraints. Within this group, two otherwise similar individuals who have different amounts of loans would have different wage paths and labor supply decisions. Such differences do not arise from the burden of loans since neither individual is financially constrained; instead, they arise because the two individuals are of different types. In contrast, compared with their counterparts with large initial assets, those with little or negative initial assets would behave differently; the magnitudes of such differences inform us

¹⁵These individuals can still invest in their human capital if they borrow a significant amount of new debt to repay their college loans. However, new debt (change in assets) is observed by us, and therefore we can infer who are most likely unable to invest in their human capital.

¹⁶One’s initial non-college loan asset and preference type may be correlated. However, after controlling for AFQT score, own education, parental education, age leaving school, and college loan, the remaining correlation may be weak, and we assume it is zero as an exclusion restriction.

of the severity of borrowing constraints, given our exclusion restriction.¹⁷

6.2.2 Auxiliary Models

Based on the identification argument above, we choose our auxiliary models to highlight the relationship between one’s wage and asset trajectories (overall and in the first 10 years of one’s career) and one’s initial asset (a_0) and total college loans (l_0). It should be noted that auxiliary regressions only serve as a succinct way to summarize the data; their coefficients should not be interpreted as causal effects. To be specific, we target the following 132 auxiliary model parameters to estimate 37 (40) structural parameters for the model with NBL (PBL).

1. First moments of wages and assets by education, large/small loan, and years of potential experience.¹⁸ Throughout our auxiliary models, an individual is said to have large (small) loans if his total college loan is above (below) the average loan level among loan borrowers within the same education group.
2. Coefficients from the OLS regression of (log) hourly wage of the following form:

$$\begin{aligned}
 \ln(\text{wage}_t) = & \quad X^w + \beta_1^w l_0 + \beta_2^w l_0^2 + \beta_3^w a_0 + t(\beta_4^w + \beta_5^w I(t = 10)) + \beta_6^w t^2 \\
 & + t(\beta_7^w + \beta_8^w I(t = 10)) I(\text{large loan}) \\
 & + t(\beta_9^w + \beta_{10}^w I(t = 10)) I(a_0 < \text{median}) \\
 & + t(\beta_{11}^w + \beta_{12}^w I(t = 10)) I(a_0 < \text{median}) I(\text{large loan}) \\
 & + \beta_{13}^w \text{expfull}_t + \beta_{14}^w I(h_t = \text{fulltime}):
 \end{aligned} \tag{7}$$

In the first row of (7): X^w captures the correlation between wages and characteristics X , β_1^w to β_3^w relate wages to the amounts of the college loan and initial asset, β_4^w to β_7^w capture wage profiles over potential years of experience (t), allowing for a break before and after the 10th year (when college loans are paid off under the standard plan). The second row to the fourth row of (7) follow the identification argument closely and capture how wage growth (overall and in the first 10 years) differs, respectively, for those with large college loans, for those with smaller initial assets, and for those with both large loans and smaller initial assets. Finally, in the last row, we use the correlations between wages and full-time job experience (expfull_t) and full-time work status to inform us of how skill production and skill prices differ between full-time and part-time jobs.

3. Coefficients in the OLS regression of asset of the following form:

$$\begin{aligned}
 \text{asset}_t = & \quad X^a + t(\beta_1^a + \beta_2^a I(t = 10)) + \beta_3^a l_0 + \beta_4^a l_0^2 \\
 & + t(\beta_5^a + \beta_6^a I(t = 10)) I(\text{large loan}) + \beta_7^a I(h_t = \text{fulltime}):
 \end{aligned} \tag{8}$$

¹⁷Only the PBL model involves parameters directly governing the borrowing constraint.

¹⁸We group every two years of potential experience in calculating these moments.

4. The fraction of full-time workers and that of non-employed individuals by education and large/small loan.

7 Parameter Estimates and Model Fit

7.1 Parameter Estimates

We report estimates of the main parameters of interest in Table 3 and the rest in Appendix A2, for both the model with natural borrowing limits (NBL) and the model with parameterized borrowing limits (PBL). Standard errors (in parentheses) are calculated via bootstrapping.

Panel A of Table 3 shows estimates of parameters governing the human capital (HK) production function. For both NBL and PBL, our estimated elasticity of HK production with respect to investment and that respect to HK stock are around 0.8. We find that Type 2 individuals are more efficient in producing HK than Type 1 individuals ($A_2 > A_1$): We also find that workers are penalized for working part time in the following sense. First, HK production when working part time is only around 75% as effective as in the case of working full time (α_2 is normalized to 1), presumably due to fewer training opportunities on part-time jobs. Second, as Panel B shows, given the same HK rented out to the market, an individual working part-time earns less than half of the annual salary as he would on full-time jobs.

Panel C shows that Type 2, the type with higher HK production efficiency, has lower disutility from work. Panel D shows the estimated parameters governing the distribution of types. Both models suggest that, ceteris paribus, the probability of being Type 2 is higher among those with larger college loans, higher own education, and higher parental education, while it is lower among those leaving school at an older age. Panel E shows that Type 2's have higher initial HK (k_0) and that conditional on X and type, those with larger loans have lower initial HK.¹⁹

Our estimates suggest that Type 2 individuals have advantages over their Type 1 counterparts in the labor market: Type 2's have higher initial HK, higher efficiency in producing HK, and lower disutility of work. To better illustrate how types differ in their observables, we use estimates in Panel D of Table 3 to calculate the distribution of types among individuals in our sample and summarize their observable characteristics by type in Table 4. About 38% (41%) of individuals are Type 2's under NBL (PBL). Among Type 2's, around 70% are college graduates, while among Type 1's, only 21% are college graduates.

Finally, Panel F of Table 3 shows that for PBL, borrowing limits are estimated to grow with both age and human capital. Under both NBL and PBL, the evolution of borrowing limits over one's lifetime depends on the endogenous evolution of one's human capital. To show how these borrowing limits evolve in the baseline, Figure 2 plots the simulated borrowing-limit profile (averaged across individuals) under NBL on the left and its counterpart under PBL on the right. While the borrowing-limit profile is hump-shaped under NBL, it is upward-sloping over one's lifetime under PBL. Moreover,

¹⁹The raw correlation between k_0 and l_0 is 0.28 (0.25) under NBL (PBL).

Table 3: Selected Parameter Estimates

	NBL		PBL	
<u>A. HK production: $k_{t+1} = (1 - \delta)k_t + \alpha_{0h}A i_t^{-1}k_t^2$</u>				
Skill depreciation rate (δ)	0.016	(0.002)	0.008	(0.002)
Elasticity wrt investment (α_1)	0.820	(0.051)	0.822	(0.016)
Elasticity wrt human capital stock (α_2)	0.804	(0.022)	0.810	(0.010)
Type 1 factor (A_1)	0.100	(0.007)	0.090	(0.002)
Type 2 factor (A_2)	0.115	(0.005)	0.100	(0.003)
Part-time factor (α_{01})	0.727	(0.020)	0.754	(0.010)
<u>B. Skill price for part-time jobs (p_1)</u>				
	0.438	(0.009)	0.425	(0.008)
<u>C. Disutility from Work</u>				
Part-time work (Type 1) (λ_{41})	5.949	(0.200)	5.850	(0.092)
Part-time work (Type 2) (λ_{42})	2.771	(0.168)	2.692	(0.046)
Full-time work (Type 1) (λ_{51})	7.292	(0.199)	6.765	(0.133)
Full-time work (Type 2) (λ_{52})	3.429	(0.181)	3.388	(0.049)
<u>D. Type distribution: $\Pr(\chi = 2) = \exp(X\theta) / (1 + \exp(X\theta))$</u>				
Constant term (θ_0)	-1.568	(0.004)	-1.270	(0.003)
College loans (unit: \$10,000) (θ_1)	0.686	(0.041)	0.764	(0.012)
$age_0 - 25$ (θ_2)	-1.273	(0.006)	-1.345	(0.002)
$age_0 - 25$ (θ_3) for 4yr college	1.637	(0.120)	1.744	(0.167)
4-yr college education (θ_4)	1.221	(0.088)	0.932	(0.003)
Parents' education = HS (θ_5)	0.198	(0.011)	0.203	(0.002)
Parents' education > HS (θ_6)	0.573	(0.039)	0.607	(0.012)
<u>E. Initial human capital (k_0)</u>				
Constant term (b_0)	3.225	(0.089)	3.359	(0.051)
Type 2 (b_1)	1.894	(0.136)	2.057	(0.031)
4-yr college degree (b_2)	1.777	(0.108)	1.301	(0.074)
age_0 (b_3)	0.133	(0.010)	0.114	(0.002)
age_0^2 (b_4)	-1.468	(0.004)	-1.434	(0.003)
AFQT score (b_5)	0.018	(0.002)	0.016	(0.002)
College loans (\$10,000) (b_6)	-0.151	(0.005)	-0.173	(0.002)
Parents' education = HS (b_7)	0.250	(0.019)	0.281	(0.019)
Parents' education > HS (b_8)	0.278	(0.022)	0.285	(0.002)
<u>F. Credit constraints: $A(k_t, t) = \exp[\phi_0 + \phi_1 age_t + \phi_2 k_t]$</u>				
Constant term (ϕ_0)	-	-	-1.005	(0.004)
Age (ϕ_1)	-	-	0.062	(0.008)
Human capital (ϕ_2)	-	-	0.012	(0.002)

Table 4: Characteristics by Type

	NBL		PBL	
	Type 1 (61.9%)	Type 2 (38.1%)	Type 1 (58.6%)	Type 2 (41.4%)
Pr(4-yr degree)	21.3%	73.5%	21.1%	69.6%
AFQT score	56.4	68.0	56.2	67.3
Pr(parent edu=HS)	46.1%	34.6%	46.4%	35.2%
Pr(parent edu>HS)	38.1%	57.9%	37.4%	57.4%
age ₀	24.54	24.55	24.59	24.47
l_0 (\$)	2,128	8,154	1,922	7,959

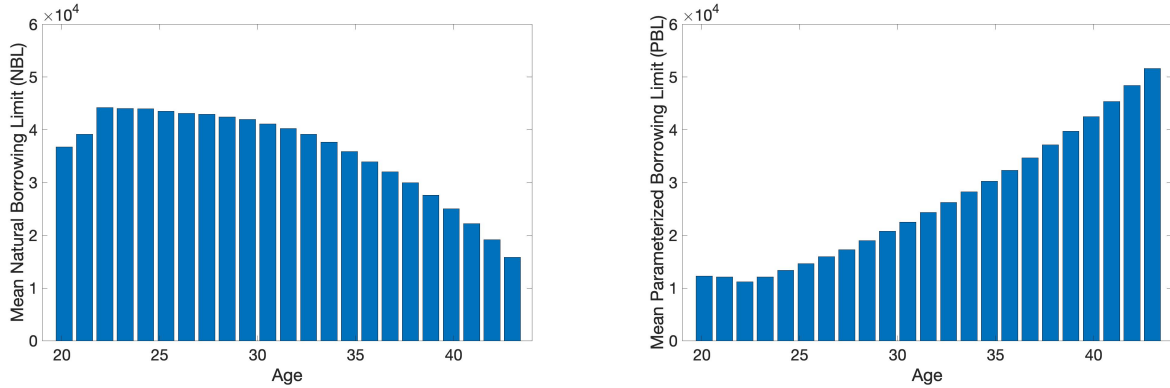


Figure 2: Borrowing Limit over time (left: NBL, right: PBL)

relative to the case under NBL, a young worker is predicted to face a tighter borrowing limit under PBL. For example, an average 20-year-old worker is estimated to be able to borrow up to \$36,780 under NBL but only up to \$12,280 under PBL. In Section 8, we examine the extent to which differences between these two models, such as that shown in Figure 2, may lead to different policy implications.

7.2 Model Fit

Figures 4, 5 and 6 in Appendix A5 report, respectively, the NBL model’s fits for profiles of full-time wages, earnings, and assets, where the horizontal axis shows years of potential experience. Figures 7, 8 and 9 show these fits for the PBL model. As described in the identification section, we are most interested in how outcomes differ between borrowers and non-borrowers and between borrowers with small initial assets (a_0) and other borrowers. Accordingly, in each figure, we present education-group specific profiles for all individuals (the left panel), for college-loan borrowers (the middle panel), and for college-loan borrowers whose initial assets are below the median within their education group (the right panel). The solid line is the data; the dotted line is the model prediction. Overall, both models are able to fit the data well; with a few exceptions, model predictions are well within the 95% confidence interval of the data (the shaded area).

8 Counterfactual Experiments

Using our estimated model, we conduct two sets of counterfactual experiments. In the first, a worker’s total college loans are unexpectedly forgiven upon his entry into the labor market (debt relief). This simulation serves two purposes: First, it quantifies the *ex post* welfare loss from the burden of college loan repayment. Second, it helps to understand the effect of similar policies that may be implemented in rare situations.²⁰

In a second set of counterfactual experiments, we study the effect of a less extreme class of repayment policies known as “Pay As You Earn” plans (PAYE), which was not available for cohorts under our study. Under PAYE, borrowers with outstanding loans are asked to pay the minimum between a fraction (α) of their discretionary income and the fixed repayment under the 10-year standard plan up to N years, after which the remaining college loan debt is forgiven. In post-schooling year t , for an individual with total college loan l_0 , his repayment $l^\theta(l_0; t)$ is given by

$$l^\theta(l_0; t) = \begin{cases} \max\{0; (y_t - (y_t - 1.5PL)g)\} & \text{if } t \leq N \\ \frac{l_0 \prod_{\tau=1}^{10} (1+r^c)^9}{(1+r^c)^{t-1}} & \text{if } t > N \end{cases} \quad (9)$$

In the minimum operator, the first row is one’s discretionary income, defined as the difference between one’s after-tax income $y_t - (y_t)$ and 150% of the poverty line PL ; bounded from below by 0;²¹ the second row is the fixed payment under the standard plan; the third row guarantees that one does not pay back more than what he owes. Various PAYE plans differ from one another mainly in policy parameters α and N ; we study two of them, labeled as PAYE₁ and PAYE₂. PAYE₁ is similar to the current policy with $\alpha = 10\%$ and $N = 20$; PAYE₂ resembles the one proposed by the Trump administration with $\alpha = 12.5\%$ and $N = 15$. That is, one pays back at a slower pace under PAYE₁ than under PAYE₂; but both PAYE plans feature slower payback than the standard 10-year plan.

To make the experiments more realistic, we allow individuals to choose between the standard repayment plan and the given PAYE and label the policy as $\max\{\text{StdPlan}, \text{PAYE}_n\}$ for $n = 1; 2$. Formally, upon entering the job market and before any wage or preference shocks are realized, a borrower makes the following choice

$$\max \left\{ E[V_1(\Omega_1)]; E[V_1^{\text{PAYE}_n}(\Omega_1)] \right\}; \text{ for } n = 1; 2 \quad (10)$$

The first term in (10) is the expected discounted lifetime value under the standard repayment plan, where $V_1(\Omega_1)$ is the period-1 value defined in (6) and the expectation is taken over period-1 wage and

²⁰For example, by July 2021, the Biden administration had canceled \$1.5 billion in student loan debt as a response to the COVID-19 pandemic.

²¹We use the federal poverty line for individual households in year 1983 (when individuals in our sample were between 19 and 27 years old), which is 11,940 in 2012 USD.

preference shocks. The second term in (10) is similarly defined, but loan repayment follows (9) under PAYE_n .

It should be noted that the goal of this paper is to quantify the distortion of college loan debt on individuals' *post-education* choices and the extent to which debt repayment programs can reduce this distortion. To serve the goal, the counterfactual repayment policy reforms *should* be unexpectedly implemented upon one's entry into the labor market; this is what we do in our experiments. Implications from our counterfactual experiments are therefore best interpreted as policy impacts on individuals whose education and college loan decisions have been made, rather than long-run impacts on cohorts who are yet to make these pre-market decisions. In the following, we examine these short-run impacts on college-loan borrowers' post-education choices, welfare, and net contribution to government revenues, predicted by both the model with natural borrowing limits (NBL) and the model with parameterized borrowing limits (PBL).²² To preview the results, both models predict qualitatively similar policy effects, because in both models, the burden of college-loan repayment interacts with the borrowing limit to distort a young worker's human capital investment and his human capital level in turn affects how much he can borrow. Quantitatively, PBL predicts larger policy effects than NBL does, because PBL predicts tighter borrowing limits for young workers than NBL does (Figure 2).²³

8.1 Post-Schooling Trajectories

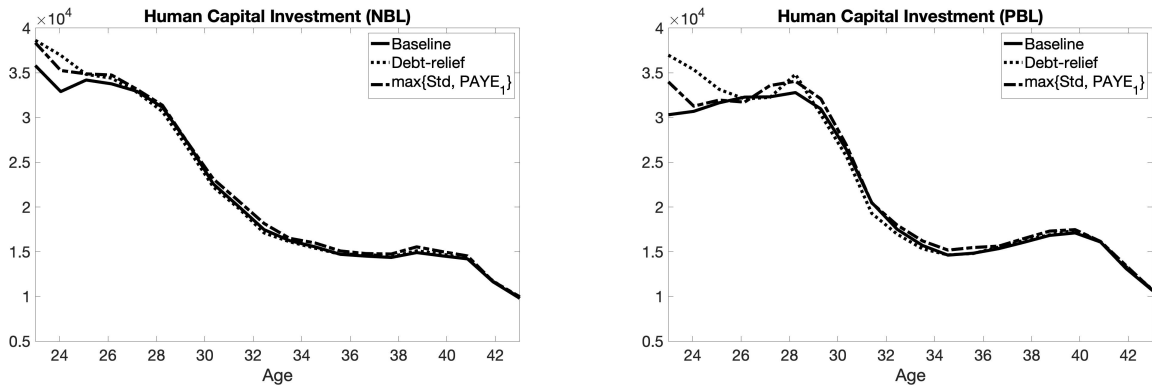
Figure 3 show the trajectories of post-education human capital investment (measured by $i_t - h_t$), annual earnings, and assets among loan borrowers by potential experience. We show these profiles in three cases—the baseline, debt relief, and $\text{max}f\text{StdPlan}$, PAYE_1g —predicted both by NBL (the left panel) and by PBL (the right panel).²⁴ Both models have qualitatively similar predictions: With either no or a lower burden of loan repayment in the counterfactual policy environment, workers invest more in their human capital early in their career. Consequently, compared to the baseline, annual earnings are lower early on but higher later in both counterfactual cases. Compared to the effects of PAYE , debt relief's effects on investment and earnings are larger at the beginning of one's career while smaller later on. As we will show in Table 5 below, one accumulates more human capital over his lifetime under PAYE than he does under debt relief; we will provide more discussion there.

Both models also predict that compared to the baseline, the average stock of assets is higher in all years under debt relief. This is expected because one is free of his college loan debt (a negative asset) under debt relief. Interestingly, the average stock of assets is slightly lower under PAYE than it is in the baseline. This is because, under PAYE , one's per-period repayment adjusts down when

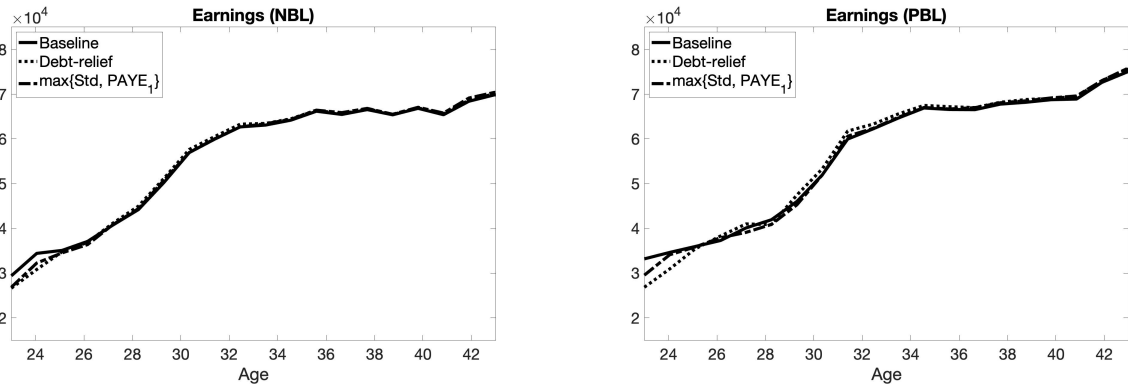
²²We focus on partial equilibrium impacts, and therefore we do not consider how these policies may affect those without college loans.

²³Hai and Heckman (2017) find that tuition policy impacts are milder in the natural borrowing limit model than they are in a model with exogenously fixed education-specific borrowing limits.

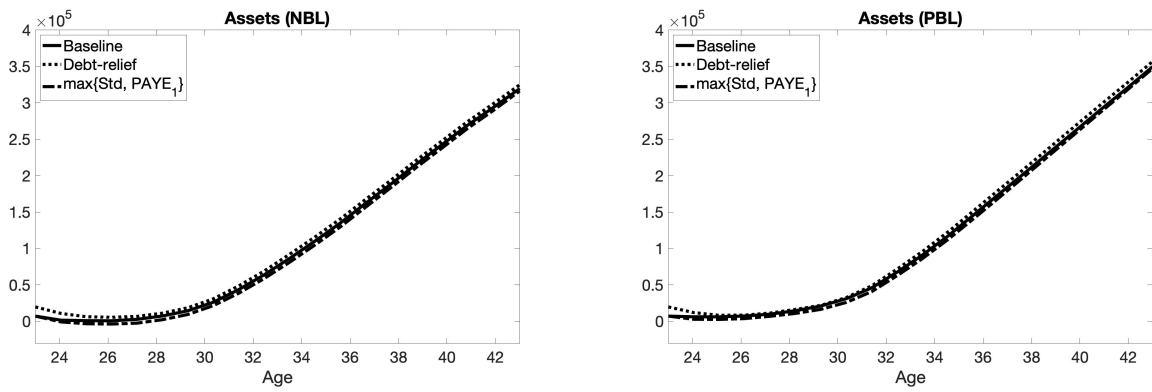
²⁴To make the graph easier to read, we do not show the profiles under $\text{max}f\text{StdPlan}$, PAYE_2g , which are very similar to those under $\text{max}f\text{StdPlan}$, PAYE_1g . Individuals enter the labor market at different ages in our sample, leading to different years of potential experience conditional on age. The graphs show the trajectories of the cohort who finished schooling at age 23. The graphs for other cohorts are similar.



(a) Human capital investment



(b) Earnings



(c) Asset

Figure 3: Lifetime earnings, assets, and human capital investment

earnings are low, which provides a borrower with insurance against bad wage shocks and weakens his precautionary savings incentive.²⁵

Table 5: Earnings, Asset, Human Capital and Forgiven Loans

Counterfactual versus baseline	Debt-Relief		maxfStdPlan, PAYE _{1g}		maxfStdPlan, PAYE _{2g}	
	NBL	PBL	NBL	PBL	NBL	PBL
Δ Annual Earnings ($t = 1$) (\$)	-1,975	-5,524	-1,623	-3,017	-1,603	-2,978
Δ Annual Earnings (<i>Age</i> 45) (\$)	210	308	518	629	507	623
Δ Asset (<i>Age</i> 45) (\$)	6,032	6,615	-2,428	-2,739	-1,078	-1,258
Δ HK (<i>Age</i> 45) (\$)	313	410	598	736	546	679
Δ Average Weekly Hours ($t = 1$ to 10)	-0.13	-0.10	-0.09	-0.05	-0.10	-0.06
Δ Average Weekly Hours ($t = 1$ to <i>Age</i> 45)	-0.08	-0.06	-0.05	-0.03	-0.05	-0.03
Borrowers with Loans (partly) Forgiven (%)	100	100	5.30	5.15	33.87	34.35
Average Forgiven Loan/Loan Forgiven >0 (\$)	12,016	12,016	13,466	12,764	4,855	5,094

Table 5 summarizes changes in outcomes among all college loan borrowers associated with each of the three counterfactual policies relative to the baseline. The first four rows show changes in earnings, assets, and human capital stock. Consistent with Figure 3, these changes are quantitatively larger under PBL than they are under NBL.²⁶ Interestingly, although college loan borrowers have more human capital at age 45 in all counterfactual scenarios than they do in the baseline, this effect is larger under PAYE policies than it is under debt relief. By forgiving one’s debt entirely, debt relief removes any distortion college loan debt may have on workers’ decisions; this implies that PAYE policies induce *overinvestment* in human capital. This is because PAYE policies operate essentially as income taxes and because one’s remaining college loan debt will be forgiven after the pre-specified loan repayment periods. As such, PAYE policies create incentives for borrowers to earn less during loan-repayment periods. The last two rows show that the reduction in one’s average weekly work hours is very small in all counterfactual scenarios, especially under PAYE. That is, rather than reducing working hours, borrowers react to PAYE and deliberately earn less in loan-repayment periods by overinvesting in their human capital, which will lead to higher human capital in the future. This prediction is in direct contrast to, for example, standard learning-by-doing models; in those models, borrowers can react to earning disincentives only by reducing their working hours, which in turn will lower their future human capital.

Finally, the last two rows of Table 5 show the fraction of borrowers whose loans are (partly) forgiven and the average amount forgiven among these borrowers. Under debt relief, all loans are forgiven for all borrowers. Under the slower-but-longer PAYE plan (PAYE₁), around 5% of borrowers fail to pay off their debt and the average amount forgiven is around \$13,000; under the faster-but-shorter PAYE plan (PAYE₂), this fraction is much higher at 34% and the average amount forgiven is around \$5,000.

²⁵Carroll (1997) and Carroll et al. (2003) provide precautionary savings motive as a reason for the seeming paradox of students underutilizing their available college loans.

²⁶Since we have normalized skill price on full-time jobs to be 1, HK is measured in \$.

8.2 Individual Welfare

To evaluate the welfare implication of a given counterfactual policy, we calculate each borrower’s annual consumption equivalent variation (CEV) from age_0 to 45, i.e., the additional annual consumption beyond his baseline consumption between the time he leaves school and age 45 that would make him indifferent between the baseline and the counterfactual scenario. Table 6 shows the annual CEV for each counterfactual policy, at the mean, the median, the 10th percentile, and the 90th percentile. In general, both NBL and PBL predict qualitatively similar welfare implications, but policy impacts are quantitatively larger under PBL.²⁷ For example, both models predict that debt relief would lead to larger gains for borrowers than PAYE policies. Under NBL, debt relief would make an average borrower better off by \$1,086 worth of annual CEV; under PBL, this figure is \$1,379. Going beyond the average CEV, Table 6 shows that the distribution of welfare gains is right-skewed (the mean is higher than the median), especially under debt relief. This is not surprising because the distribution of loans is right-skewed: The small fraction of individuals with large loans would disproportionately benefit from these counterfactual loan repayment policies. Comparing between the two PAYE plans, we find that welfare gains are slightly bigger under the faster-but-shorter plan (PAYE₂). The last two columns of Table 6 present another counterfactual policy— $maxfStdPlan$, PAYE₁, PAYE₂ g —that allows individuals to choose from three options upon entering the labor market: the standard plan, PAYE₁, and PAYE₂. The average annual CEV for this policy is \$380 under NBL and \$486 under PBL.

Table 6: Annual Consumption Equivalence Variation

	Debt Relief		$maxfSPlan$, PAYE ₁ g		$maxfSPlan$, PAYE ₂ g		$maxfSPlan$, PAYE ₁ , PAYE ₂ g	
	NBL	PBL	NBL	PBL	NBL	PBL	NBL	PBL
Mean	1,086	1,379	347	439	366	473	380	486
10th pctl	170	193	71	145	74	160	76	160
Median	674	819	251	334	283	371	284	371
90th pctl	2,203	2,816	497	731	585	787	585	790

To the extent that individuals differ in their initial conditions, including their college loan amounts, they may prefer different loan repayment plans. Table 7 shows the fraction and characteristics of individuals by their preferred plan when they can choose between the standard plan and PAYE₁ (the left panel) and also when they can choose between the standard plan and PAYE₂ (the right panel). Over 94% of borrowers prefer either PAYE plan over the standard plan under NBL; almost all individuals do so under PBL.²⁸ In general, the small fraction of borrowers who prefer the standard plan have larger amounts of college loans than those who prefer PAYE, which may be surprising because larger loans imply heavier burdens of repayment. However, this finding arises from the correlation between college loan amounts and individual traits: Relative to other borrowers, those who prefer the

²⁷This is in line with Hai and Heckman (2017), who find that tuition policy impacts are milder in the natural borrowing limit model than they are in a model with exogenously fixed education-specific borrowing limits.

²⁸In Appendix Tables 10 and 11, we show borrowers’ preference ranking of all three plans: PAYE₂ is the most preferred plan for 56% (89%) of borrowers under NBL (PBL).

standard plan are more likely to have higher initial human capital and to be Type 2 individuals, who have higher efficiency in producing human capital and lower work disutility. That is, these borrowers have greater earnings potentials; for them, it is better to pay back the loan faster rather than delaying and paying more interest.

Table 7: Who Chooses Which?

	max f StdPlan, PAYE ₁ g				max f StdPlan, PAYE ₂ g			
	StdPlan		PAYE ₁		StdPlan		PAYE ₂	
	NBL	PBL	NBL	PBL	NBL	PBL	NBL	PBL
Percent	5.88%	0.69%	94.12%	99.31%	5.99%	0.01%	94.01%	99.99%
loan ₀ (\$)	27,036	20,276	11,078	11,958	26,126	37,311	11,117	12,013
Pr(Type 1)	18.0%	1.5%	45.6%	40.8%	20.1%	100.0%	45.5%	40.6%
Pr(4-year college)	88.9%	100.0%	62.5%	63.8%	87.3%	100.0%	62.6%	64.0%
Pr(parent edu = HS)	39.9%	1.5%	40.5%	40.8%	39.1%	100.0%	40.6%	40.5%
Pr(parent edu > HS)	51.5%	98.5%	52.2%	51.8%	52.4%	0.0%	52.1%	52.2%
initial HK k_0	75,407	64,801	61,150	60,622	75,343	37,803	61,137	60,653
AFQT score	77.9	72.0	70.1	70.6	77.3	49.0	70.2	70.6
age ₀	21.8	23.7	25.5	25.3	21.6	28.0	25.6	25.3
initial net asset (\$)	3,775	-18,315	19,478	18,813	5,513	225,095	19,386	18,533

8.3 Government Revenue

Finally, we evaluate the impacts of different counterfactual policies on the government budget, including the direct change in loan payment and the indirect change in income tax revenues arising from changes in borrowers' lifetime earnings. For this calculation, we need to make some assumptions about the evolution of workers' human capital beyond age 45. These assumptions only affect the calculation of the government budget, not the calculation of individuals' welfare we presented above. We have calculated the government budget under eight different assumptions; as shown in Appendix A3.2, our policy implications are robust. In Table 8, we present results from a relatively conservative case (in terms of revenue gains). In this case, individuals work full-time between ages 45 and 60, and then part-time until retirement at age 62; they invest just enough to keep their human capital constant between ages 45 and 55, and their human capital depreciates at the estimated depreciation rate between 55 and 62.

For each counterfactual policy, Table 8 presents changes in the discounted per-borrower tax revenue and loan repayment relative to the baseline. Summing up the first two rows, row 3 shows the change in the discounted net government revenue per borrower. The last row combines changes in government budget and an average borrower's consumption equivalent variation (CEV) from $t = 1$ to age 45, both discounted to the present value (PV). For debt relief, NBL (PBL) predicts that the net government revenue would decrease by \$10,224 (\$9,094) per borrower, but this loss is outweighed by borrowers' welfare gains. Summing up government budget and borrowers' welfare, the last row shows that debt

relief would lead to a gain of \$4,974 under NBL and \$11,009 under PBL.

Table 8: Government Budget (Present Value)

	Debt-Relief		$\max fSPlan, PAYE_1 g$		$\max fSPlan, PAYE_2 g$		$\max fSPlan, PAYE_1, PAYE_2 g$	
	NBL	PBL	NBL	PBL	NBL	PBL	NBL	PBL
ΔTax	1,792	2,922	3,448	4,421	3,227	4,171	3,255	4,121
$\Delta LoanRepay$	-12,016	-12,016	-2,443	-2,403	-3,112	-3,265	-3,105	-3,509
$\Delta Budget$	-10,224	-9,094	1,005	2,018	115	906	149	612
$\Delta CEV + \Delta Budget$	4,974	11,009	5,607	8,266	5,089	7,804	5,275	7,638

For all three PAYE policies, both models predict that despite losses in loan repayment, increases in borrowers’ lifetime earnings and hence increases in income taxes are large enough to lead to gains in government net revenues. That is, all three PAYE policies lead to a win-win situation, where individual borrowers are better off and government net revenues also increase. Comparing across all three PAYE policies, government net revenues increase the most under PAYE₁. As shown previously, most borrowers prefer the faster-but-shorter plan (PAYE₂) over the slower-but-longer plan (PAYE₁); however, welfare gains are similar in magnitude across all three PAYE policies (Table 6). As a result, if one were to judge policy impacts based on a simple sum of government net revenues and borrowers’ welfare, PAYE₁ would lead to the highest total welfare gain among the three PAYE policies.

9 Conclusion

We have developed and estimated two versions of a dynamic decision model—one with natural borrowing limits and the other with parameterized borrowing limits—to study the potential distortion of college loan debt on workers’ post-schooling trajectories. Our counterfactual simulations from both versions of the model suggest that, when they are allowed to pay back college loans at a more reasonable pace under PAYE policies, individuals will invest more in human capital and earn less in the early years of their careers to yield higher lifetime earnings. We find evidence that PAYE policies create earnings disincentives, leading borrowers to overinvest in their human capital in loan-repayment periods. As a result, loans will be partially forgiven for some individuals. Despite losses in loan repayment, increases in borrowers’ lifetime earnings and hence increases in income taxes are large enough to lead to gains in government net revenues. That is, PAYE policies create a win-win situation for both individual borrowers and the government.

Given our focus on the distortion of college loan debt on individuals’ *post-education* choices, we have taken individuals’ pre-market decisions as pre-determined and found that individuals with larger college loans are more likely to have higher efficiency in producing human capital and lower disutility for work. A natural extension is to incorporate the well-studied education and college loan choices into our model. This extension will enable one to study the long-term impact of loan repayment policies for not only cohorts whose education decisions have been made but also cohorts who are yet to make

those decisions.

Given data limitations, we have assumed a common standard repayment plan in our baseline model, which is in line with the policy environment for cohorts under our study. As quantified in our counterfactual analysis, giving more loan repayment options to individuals will weakly improve their welfare, since there is no single plan that works best for all. However, in the current policy debate, some argue against the coexistence of multiple PAYE plans in fear that it may be confusing. To verify such an argument, one can extend our current framework to allow for some friction and/or psychic cost associated with choosing among repayment plans. Given individual-level data on their repayment plan choices and career trajectories, one can quantify these psychic costs, which may be useful for the design of college loan repayment policies.

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Appendix

A1. Detailed Functional Forms

A1.1 Type and Initial Human Capital An individual's type is correlated with his total college loans (l_0), initial asset level (a_0), age leaving school (age_0), education level (e) and parental education (e^p) such that

$$\Pr(\text{type} = 2j|X) = \frac{\exp(f(X))}{1 + \exp(f(X))};$$

where

$$f(X) = \beta_1 l_0 + \beta_2 a_0 + \sum_{m=1}^{\infty} \beta_{2+m} I(age_0 > 22) I(e = m) + \sum_{m=1}^{\infty} \beta_{4+m} I(e = m) + \sum_{m=2}^{\infty} \beta_{5+m} I(e^p = m);$$

An individual's initial human capital level k_0 is a function of his type, education, initial age, AFQT score, parental education and the amount of one's college loans:²⁹

$$k_0 = \beta_1 I(\text{type} = 2) + \sum_{m=1}^{\infty} \beta_{1+m} I(e = m) + \sum_{m=1}^{\infty} \beta_{3+m} I(age_0 > 22) I(e = m) + \beta_6 AFQT + \beta_7 l_0 + \sum_{m=2}^{\infty} \beta_{6+m} I(e^p = m);$$

A1.2 Terminal Value Function

$$V(a_T; k_T; \text{type}; X) = \beta_1 a_T + \beta_2 a_T^2 + \sum_{m=1}^{\infty} \beta_{2+m} I(\text{type} = m) k_T + \sum_{m=1}^{\infty} \beta_{4+m} I(\text{type} = m) k_T^2 + \beta_7 a_T k_T;$$

A1.3 Wage Distribution As specified in Equation (2); earnings are given by $y_t = \rho_{h_t} k_t (1 - \delta_t) e^t$: We model the shock as $\delta_t = e_t - E(e)$: Following Hai and Heckman (2017), we assume wage shocks e_t are i.i.d. draws from a gamma distribution, the probability density function of which is given by

$$f(e_t; a; b) = \frac{1}{\Gamma(a)b^a} e_t^{a-1} e^{-e_t/b};$$

The density function is governed by two parameters: the shape parameter a and the scale parameter b . Without loss of generality, the lowest possible e_t is normalized to 0 for all t .

A2. Parameter Estimates

Additional parameter estimates are presented in Table 9.

²⁹Our model does not distinguish between various channels through which such dependence exists. Some examples include: 1) the cost of education may be associated with the quality of education within an education group, 2) individuals may take loans based on their ability levels.

Table 9: Other Parameter Estimates

	NBL		PBL	
Utility scale parameter (v)	2.811	(0.043)	2.812	(0.026)
<u>Terminal Value (at age 45)</u>				
Asset (γ_1)	8.673	(0.425)	9.271	(0.330)
Asset ² (γ_2)	-0.041	(0.007)	-0.032	(0.005)
Human capital (Type 1) (γ_3)	1.843	(0.152)	2.165	(0.034)
Human capital ² (Type 1) (γ_4)	-0.001	(0.008)	-0.001	(0.003)
Human capital (Type 2) (γ_5)	3.440	(0.172)	3.580	(0.092)
Human capital ² (Type 2) (γ_6)	-0.001	(0.008)	-0.001	(0.002)
Asset human capital (γ_7)	-0.031	(0.012)	-0.037	(0.002)
<u>Wage Distribution^a</u>				
Shape of Gamma Distribution (a)	40.018	(2.919)	40.104	(0.622)
Scale of Gamma Distribution (b)	0.050	(0.003)	0.050	(0.002)

^a With the estimated parameters of the gamma distribution, the mean is 2.00 and the standard deviation is 0.32 for NBL, while the mean is 2.01 and the standard deviation is 0.32 for PBL.

A3. Counterfactual

A3.1 Rankings Among Three Policies We present, in Tables 10 and 11, rankings and who choose which plan among three policies (standard plan, PAYE₁, PAYE₂).

Table 10: Ranking f StdPlan, PAYE₁, PAYE₂ g

			NBL	PBL
PAYE ₂	PAYE ₁	StdPlan	56.24%	88.73%
PAYE ₂	StdPlan	PAYE ₁	0.25%	0.68%
StdPlan	PAYE ₁	PAYE ₂	5.52%	0.00%
StdPlan	PAYE ₂	PAYE ₁	0.10%	0.01%
PAYE ₁	PAYE ₂	StdPlan	37.52%	10.58%
PAYE ₁	StdPlan	PAYE ₂	0.36%	0.00%

A3.2 Government Budget under Different Assumptions We evaluate the impacts of different counterfactuals on the government budget under eight different assumptions about the evolvement of human capital and work status beyond T (age 45) until retirement (age 62) and present the results in Table 12:

Case 1: individuals work full-time until retirement at age 62, invest just enough to keep k constant until age 55 and invest 0 afterwards.

Table 11: Who choose which plan - $\max f$ StdPlan, PAYE₁, PAYE₂ g

	StdPlan		PAYE ₁		PAYE ₂	
	NBL	PBL	NBL	PBL	NBL	PBL
Percent	5.63%	0.01%	37.88%	10.58%	56.49%	89.41%
loan ₀ (\$)	26,653	37,311	10,951	20,624	11,273	10,995
Pr(type 1)	18.6%	100.0%	47.2%	32.7%	44.4%	41.5%
Pr(4-year college)	88.4%	100.0%	56.9%	68.8%	66.4%	63.5%
Pr(parent edu = HS)	41.7%	100.0%	44.4%	36.4%	37.8%	41.0%
Pr(parent edu > HS)	49.3%	0.0%	48.2%	51.3%	55.1%	52.3%
initial HK k_0	75,682	37,803	63,393	57,495	59,682	61,027
AFQT	77.1	49.0	69.7	65.2	70.6	71.2
age ₀	21.6	28.0	24.6	32.7	26.2	24.4
initial net asset (\$)	5,194	225,095	20,457	32,921	18,610	16,830

Case 2: individuals work full-time until retirement at age 62, invest 0 in k after 45.

Case 3: individuals work full-time until retirement at age 62, invest just enough to keep k constant until age 50 and invest 0 afterwards.

Case 4: individuals work full-time until retirement at age 62, invest $i_t = 0.1$ between 45 and 55 and invest 0 afterwards.

Case 1⁰ to Case 4⁰ are counterparts of Case 1 to Case 4, but individuals work only part-time past age 60.

Table 12: Government Budget - Other Scenarios (Present Value)

	$\max f$ StdPlan, PAYE ₁ g				$\max f$ StdPlan, PAYE ₂ g				$\max f$ StdPlan, PAYE ₁ , PAYE ₂ g			
	Δ Budget		Δ CEV+ Δ Budget		Δ Budget		Δ CEV+ Δ Budget		Δ Budget		Δ CEV+ Δ Budget	
	NBL	PBL	NBL	PBL	NBL	PBL	NBL	PBL	NBL	PBL	NBL	PBL
<i>Case1</i>	1,327	2,440	5,930	8,688	412	1,298	5,386	8,196	449	999	5,575	8,025
<i>Case2</i>	1,406	2,474	6,009	8,722	484	1,328	5,458	8,226	522	1,030	5,648	8,055
<i>Case3</i>	1,398	2,477	6,000	8,726	476	1,332	5,451	8,230	514	1,033	5,640	8,059
<i>Case4</i>	1,387	2,418	5,989	8,666	466	1,277	5,440	8,175	504	979	5,630	8,005
<i>Case1</i> ⁰	1,005	2,018	5,607	8,266	115	906	5,089	7,804	149	612	5,275	7,638
<i>Case2</i> ⁰	1,131	2,082	5,733	8,330	230	964	5,204	7,862	266	670	5,392	7,696
<i>Case3</i> ⁰	1,100	2,070	5,702	8,318	202	954	5,176	7,852	238	660	5,364	7,686
<i>Case4</i> ⁰	1,088	1,994	5,690	8,243	191	884	5,165	7,782	226	590	5,352	7,616

A4. Natural Borrowing Limit In deriving the natural borrowing limit, Hai and Heckman (2017) consider the consumption level that makes a worker indifferent between $h_t \geq f_1; 2g$ and $h_t = 0$ such that, under the most unfavorable possible income shocks, earnings beyond this consumption level can be enforced to be paid back to the lender. We extend this concept to account for workers' optimal choices of employment $h \geq f_0; 1; 2g$ and investment $i \geq [0; 1]$: Denote $C_t^{ev}(h; i; l_0; ; k_t)$ as the $(h; i)$ -

specific consumption compensation at time t for a worker with state variables $(l_0; i; k_t)$, which is the consumption level that makes him indifferent between choosing $(h; i)$ and not working ($h = 0$) at t (before the realization of transitory labor supply taste shocks). $C_t^{ev}(h; i; l_0; i; k_t)$ is implicitly defined by

$$u(C_t^{ev}(h; i; l_0; i; k_t); h; \underline{y}) + E[V_{t+1}(\Omega_{t+1}|\Omega_t; a_{t+1} \quad l_{t+1} = B_t(l_0; k_{t+1}; \underline{y}); k_{t+1} = (1 - \delta)k_t + \theta h A i^{-1} k_t^2)] \\ = u(\underline{c}; h = 0; \underline{y}) + E[V_{t+1}(\Omega_{t+1}|\Omega_t; a_{t+1} \quad l_{t+1} = B_t(l_0; k_{t+1}; \underline{y}); k_{t+1} = (1 - \delta)k_t)]: \quad (11)$$

We define the endogenous borrowing limit at t recursively by the following:

$$B_{t-1}(l_0; k_t; \underline{y}) = \frac{B_t(l_0; k_{t+1}; \underline{y}) \max_{h \geq 0} [p_h k_t (1 - \delta) e^{-\beta} C_t^{ev}(\tilde{h}; \tilde{i}; l_0; i; k_t) g]}{1 + r^b} \quad (12)$$

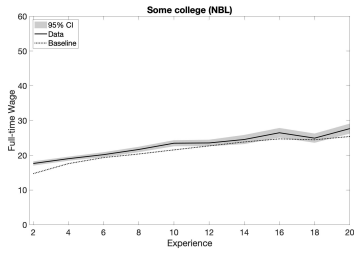
$$\tilde{h}; \tilde{i} = \arg \max_{h \geq 0, i \in [0, 1]} f l(h > 0) [p_h k_t (1 - \delta) e^{-\beta} C_t^{ev}(h; i; l_0; i; k_t)] g g \quad (13)$$

$$k_{t+1} = (1 - \delta)k_t + \theta h A i^{-1} k_t^2; \quad (14)$$

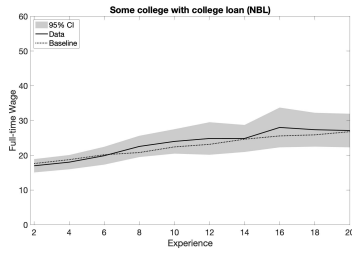
where \underline{y} is the most unfavorable income shock.³⁰ For the last period, we set $B_T(\cdot)$ at the third percentile of the asset distribution among those aged 43 to 47 in our sample, which is \$8,531. Then we calculate the natural borrowing limit from $t = T$ to $t = age_0$ using equations (11) to (14) recursively.

A5. Model Fit Figures 4 to 9 present the model fit. In each figure, we present education-group specific profiles for all individuals (the left panel), for college-loan borrowers (the middle panel), and for college-loan borrowers whose initial assets are below the median within their education group (the right panel). The solid line is the data; the dotted line is the model prediction. Overall, both models are able to fit the data well; with a few exceptions, model predictions are well within the 95% confidence interval of the data (the shaded area).

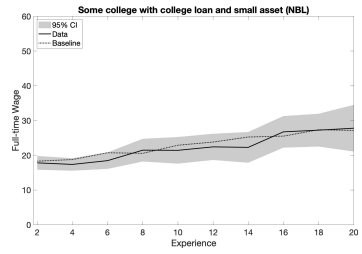
³⁰These equations imply that if $p_h k_t (1 - \delta) e^{-\beta} C_t^{ev}(h, i; l_0, \chi, k_t) < 0$ for $h > 0$, then $\hat{h} = 0$ and $B_t(l_0, k_t, \chi) = \frac{B_{t+1}(l_0; k_{t+1}; \underline{y})}{1 + r^b}$.



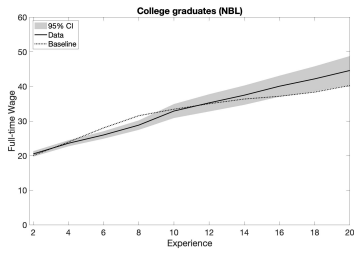
(a) Some college



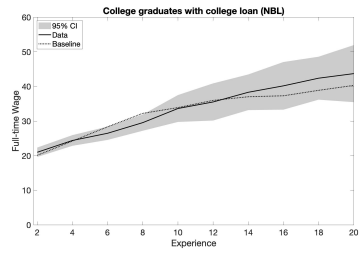
(b) Some college with college loan



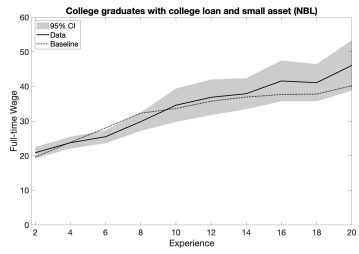
(c) Some college with college loan and small asset



(d) College graduates

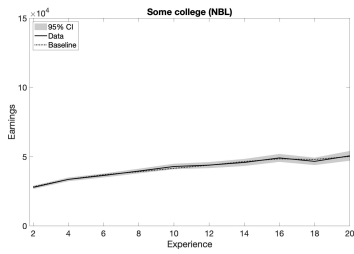


(e) College graduates with college loan

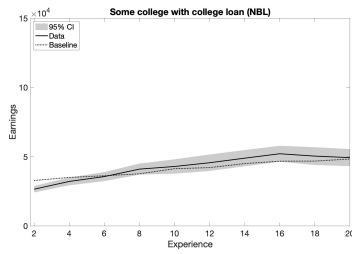


(f) College graduates with college loan and small asset

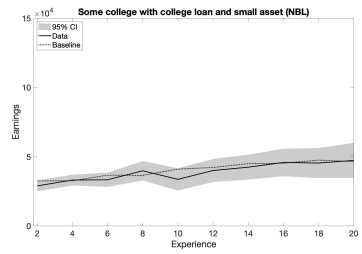
Figure 4: Model Fit: Full-time Hourly Wage by Potential Experience (NBL)



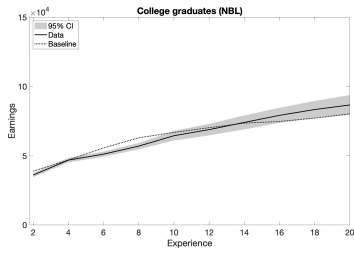
(a) Some college



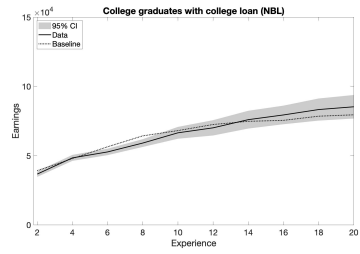
(b) Some college with college loan



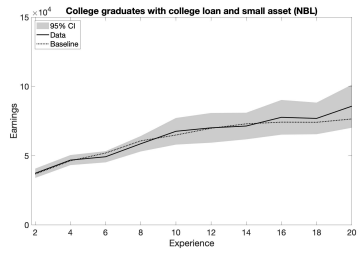
(c) Some college with college loan and small asset



(d) College graduates



(e) College graduates with college loan



(f) College graduates with college loan and small asset

Figure 5: Model Fit: Annual Earnings by Potential Experience (NBL)

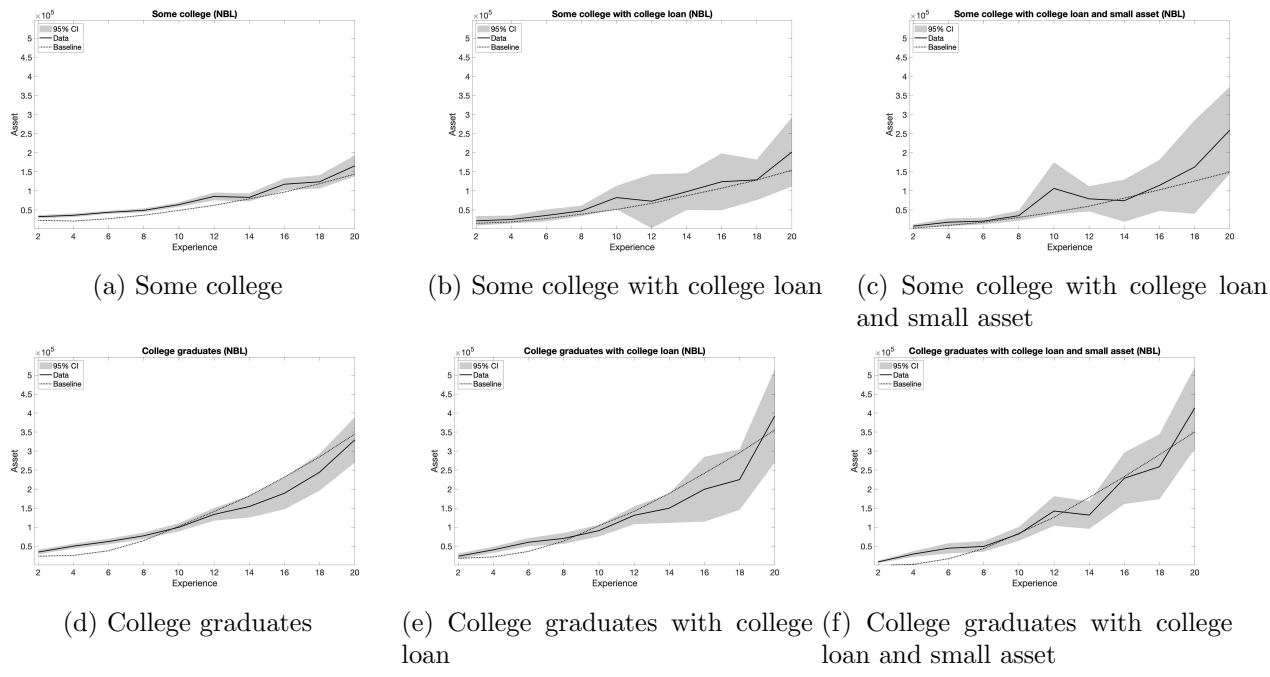


Figure 6: Model Fit: Assets by Potential Experience (NBL)

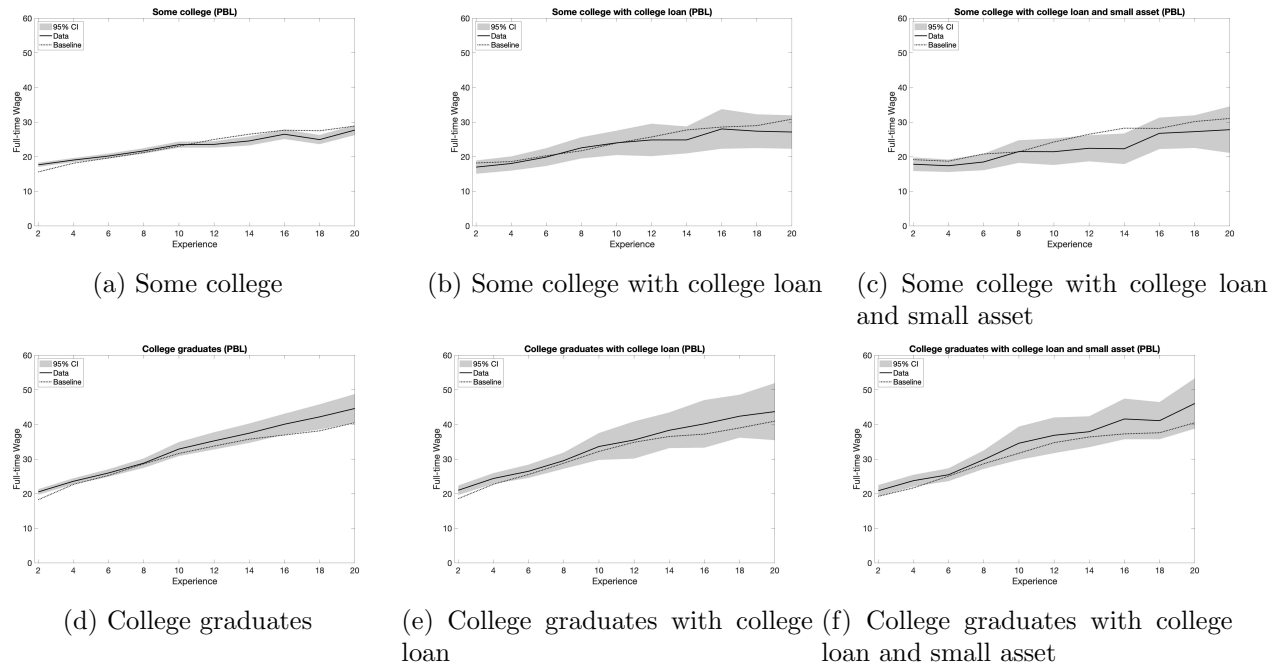
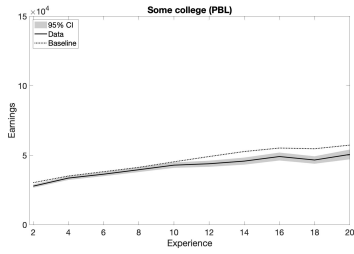
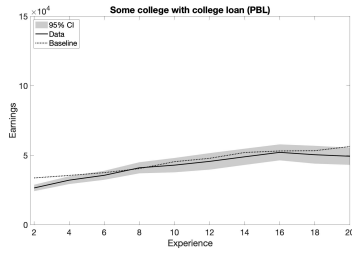


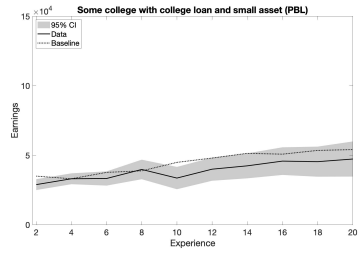
Figure 7: Model Fit: Full-time Hourly Wage by Potential Experience (PBL)



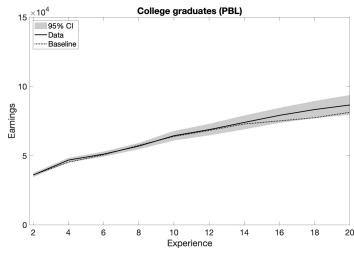
(a) Some college



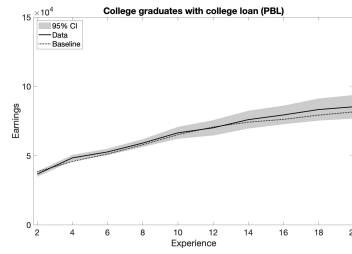
(b) Some college with college loan



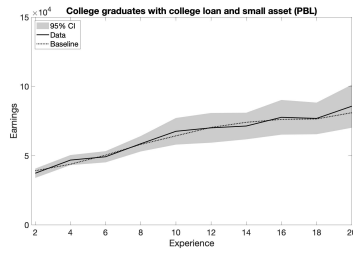
(c) Some college with college loan and small asset



(d) College graduates

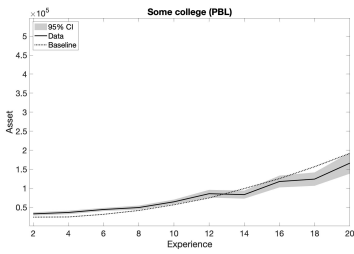


(e) College graduates with college loan

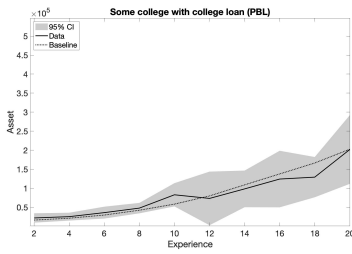


(f) College graduates with college loan and small asset

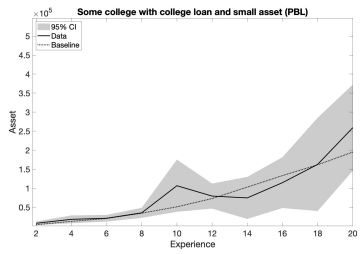
Figure 8: Model Fit: Annual Earnings by Potential Experience (PBL)



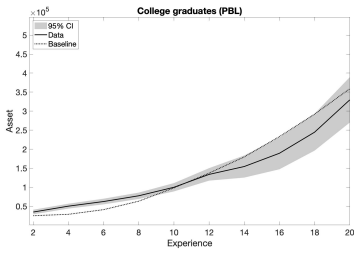
(a) Some college



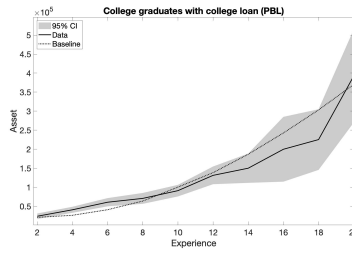
(b) Some college with college loan



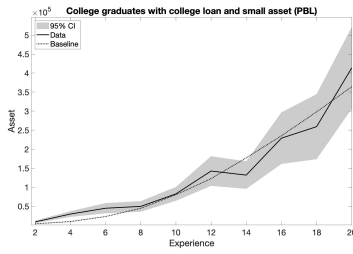
(c) Some college with college loan and small asset



(d) College graduates



(e) College graduates with college loan



(f) College graduates with college loan and small asset

Figure 9: Model Fit: Assets by Potential Experience (PBL)

Online Appendix (Not for Publication)

B. Model Solution

We solve the model numerically by backward induction. Individual heterogeneity at time t in the model is characterized by $(a_t; k_t; X_t)$. The variables are discretized as follows: the asset levels (a_t) are discretized using 25 grid points. The human capital levels (k_t) are discretized using 10 points. The amounts of unpaid loans are discretized using five points. The starting age is grouped into intervals of five, which results in four starting-age groups. With two unobserved types, this classification amounts to 10,000 possible state points that represent individual heterogeneity. With the state space discretized, we can solve the model for each individual who belongs to one of mutually exclusive groups defined by $(a_t; k_t; X_t)$.

Continuous choice variables (asset (a) and human capital investment (i)) are discretized. An individual can choose the asset level in the next period a_{t+1} from the set $\{a, \dots, \bar{a}\}$, subject to the asset lower bound given by $A(k_t; age_t)$. We need to interpolate the value function since the human capital level and/or the unpaid loan level in the next period could be at a value between the value functions evaluated on the grid. When the new level of human capital associated with a chosen amount of investment is at a value between two grid points, we apply linear interpolation.

B.1. Further Details

Since the preference shocks follow an i.i.d. Type I extreme value distribution, the decision problem at time t , given $(a_{t+1}; c_t; i_t; t)$, can be written in recursive form as

$$V(\Omega_t; a_{t+1}; c_t; i_t; t) = \max_h \tilde{v}(x_t; h; a_{t+1}; c_t; i_t; t) + \beta V_{t+1}$$

where

$$\tilde{v}(x_t; h) = u(c_t; h; i_t; t) + \beta E[V_{t+1}(\Omega_{t+1})]$$

Denote $\bar{v}(x_t) = E[\tilde{v}(x_t; h)]$, where x consists of all the necessary state variables. Following McFadden (1974) and Rust (1987), we have

$$\bar{v}(x_t) = -\gamma + \log \int_{h=0}^{\infty} \exp(\tilde{v}(x_t; h)) dF(h)$$

where γ is the Euler constant.

Using the above solution, the value function can now be expressed by

$$E[V_{t+1}(\Omega_{t+1}; a_{t+2}; c_{t+1}; i_{t+1})] = \int \bar{v}(x_{t+1}; h) dF(h)$$

The integrals over wage shocks are calculated by approximation through Monte Carlo integration.

With preference shocks following a Type I extreme value distribution, the choice-specific probabilities take a logit form:

$$P(h_t = h | a_t; k_t; \bar{l}; X;) = \frac{\exp \tilde{v}(a_t; k_t; \bar{l}; X; ; h_t = h)}{h^{2f_0; 1, 2g} \exp \tilde{v}(a_t; k_t; \bar{l}; X; ; h_t = h^l)}$$

The obtained probability is used to solve for the value function and simulate the model.

C. Sensitivity of the Objective Function with Respect to Parameters

Figures 10 and 11 show the sensitivity of the objective function value with respect to each of the model parameters for the NBL and PBL versions, respectively. For a 1% change in each parameter, the change in the objective value ranges from 0.3% to 7.7% (the figure is truncated at 3% on the right), suggesting that the objective function is not flat around the estimated parameter values.

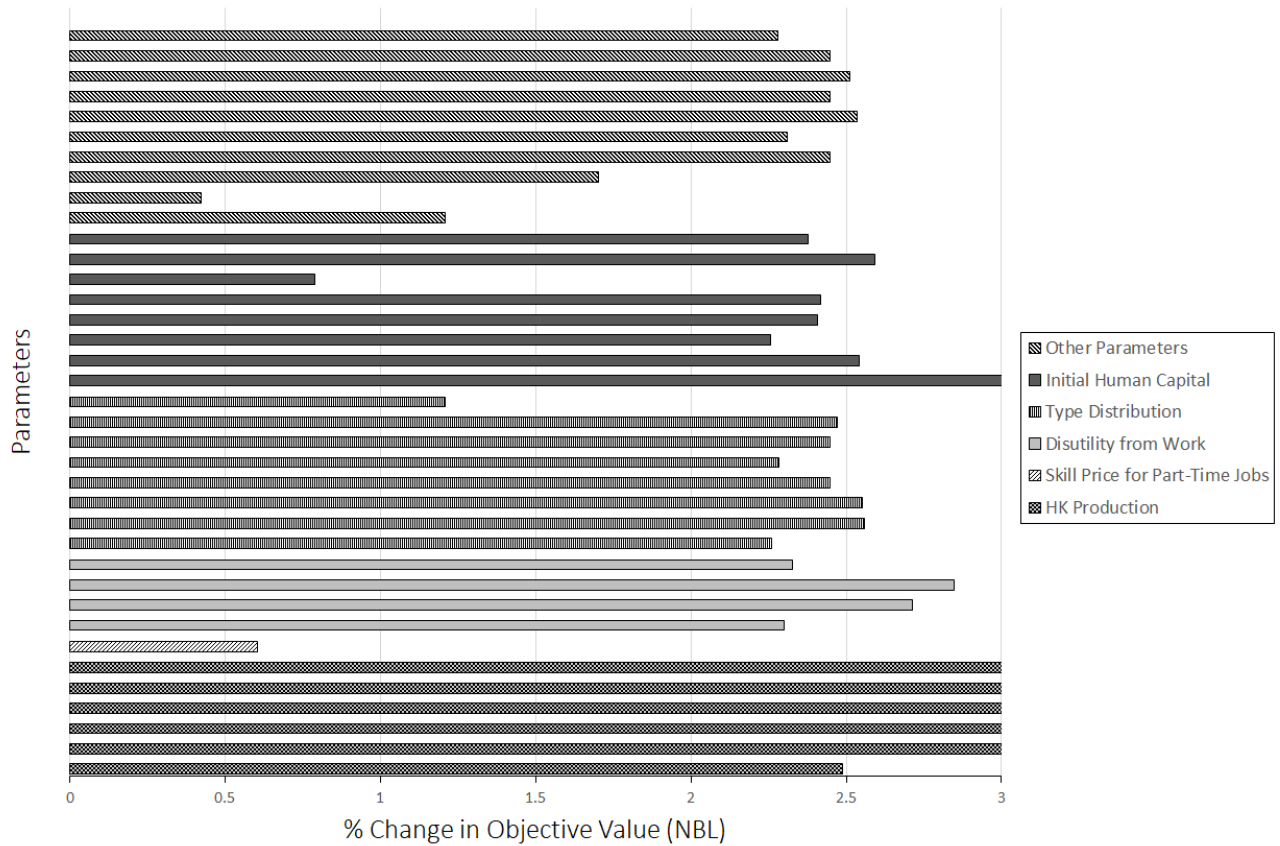


Figure 10: Sensitivity of the Objective Function (NBL)

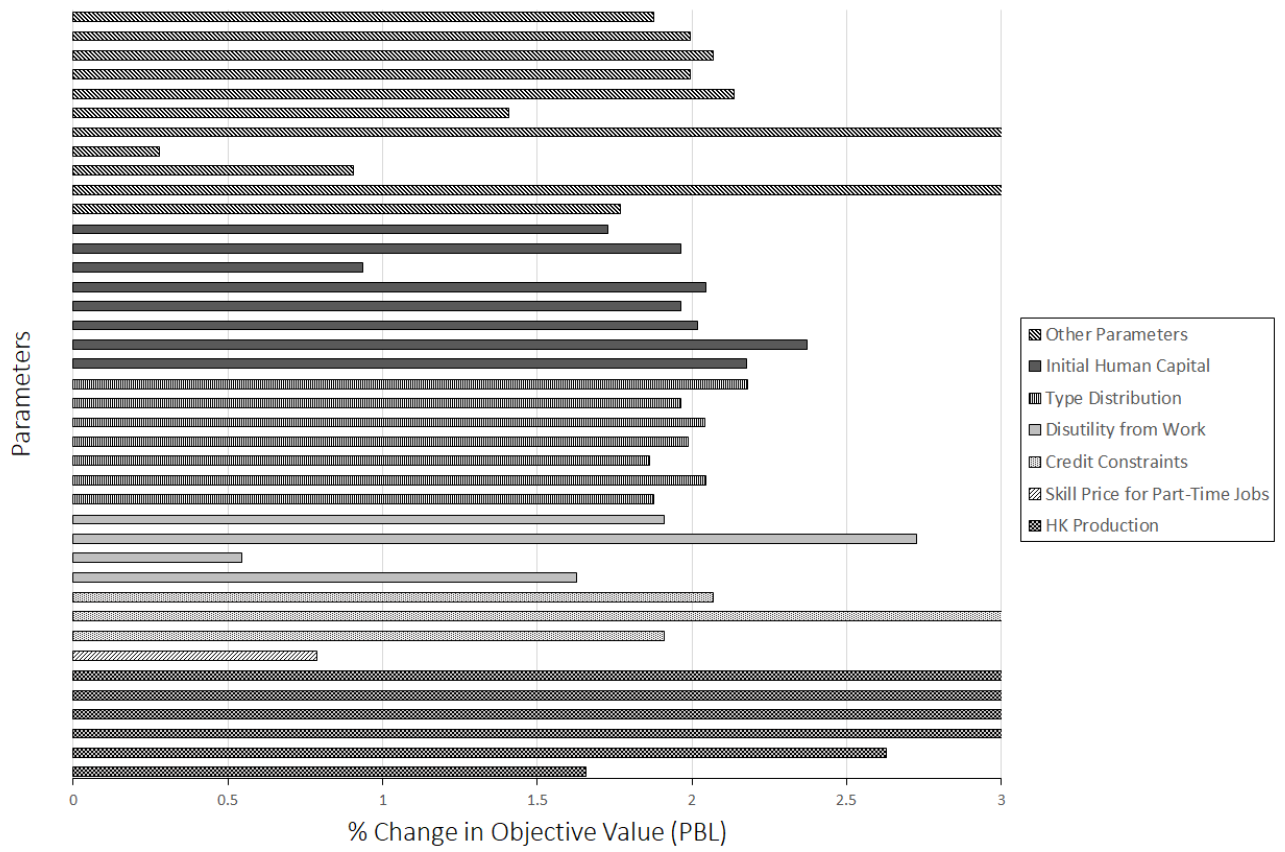


Figure 11: Sensitivity of the Objective Function (PBL)