Go Big or Buy a Home:
The Student Debt Overhang*

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Exploiting supply-side variations in college grants, we document that student debt decreases post-bachelor school enrollment and earnings growth, but does not delay first-time home ownership. This is consistent with the implications of a life-cycle human capital model with student debt overhang. High debt balances distort career choices because returns to further education depend on current income. Student debt impacts home ownership in two ways. First, it deters it via the traditional wealth channel. Second, it might increase it if it induces giving up further education and early labor market entry. Finally, we show that the impact of student borrowing on graduates' choices is due in part to the design of US student loans.

JEL codes: I22, E24, J32, J38, R21
Keywords: Student Loans, Human Capital, Housing.

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1. Introduction

This paper shows that choices on education, career, and housing are intertwined, and young workers pick different bundles depending on the conditions under which they enter the labor market. We leverage on an experiment involving the role of student loans in the United States to study the role of initial wealth levels in shaping education, career and housing choices.

Student loans have become commonplace for bachelor's degree recipients in the United States. Between 1993 and 2016, the percentage of students who had borrowed at any time during their undergraduate degree rose from 45 percent to 68 percent (Figure 1). In that time, the median cumulative amount borrowed rose from $\$14,329$ to $\$29115$ (in 2020 US dollars).[1] Student debt is now more likely to be a relevant factor young workers take into account in their decisions after graduating from college.[2]

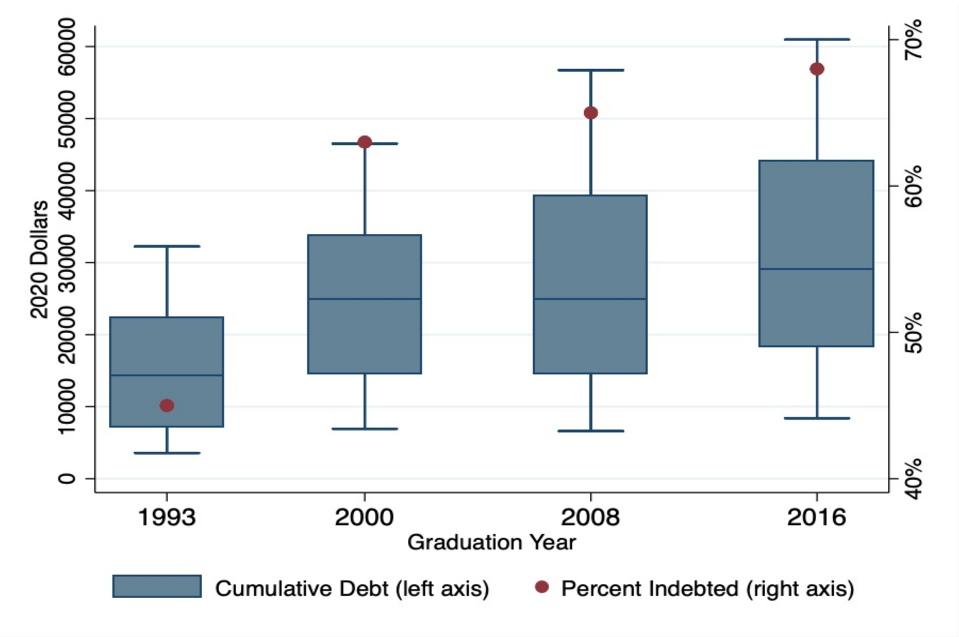
We provide evidence on the causal effect of student loans on labor market outcomes and on two of the most important post-graduation choices: career and housing. We look at how student debt affects graduates' employment, earnings, post-bachelor enrollment, and first time home ownership at different time horizons after graduation. Using supply-side variations in institution-level grants availability as an instrumental variable, we find that graduating with more debt causes a significant and persistent under-investment in human capital and education, lower earnings growth, but no significant delay in first-time home ownership. A 10 p.p. increase in student debt balances at graduation leads to a decrease of 5 p.p. in the likelihood of holding a post-bachelor degree and a 2.6 p.p. decrease in annual earnings after ten years.

A reasonable strategy to interpret our reduced form estimates is to build and estimate a life cycle model that captures variation in the data as closely as possible. We thus introduce a Roy Model (Borjas 1987) with housing and education choices, and with endogenous human capital accumulation in the spirit of Ben-Porath (1967). The estimated model shows that, while individuals deal with housing primarily as a long-term asset with monetary returns, investments in education

[1] Increasing student debt has been the result of a combination of both demand and supply factors. Between 1993-2016, median real net cost of college increased by 25% for 4-year college seniors (see Figure 11). In addition, increasing student debt can also be attributed to the passage of the Higher Education Amendments of 1992, which increased loan limits and expanded eligibility in loan programs. In the Ensuring Continued Access to Student Loans Act of 2008, the student loan limit was further increased.

[2] Real incomes for bachelor's degree recipients rose as well. However, monthly student loan payment as a percent of monthly income (one year after graduation) increased between 1993 and 2016 (see Figure 12).

Figure 1: Evolution of Student Debt
(bachelor's degree graduates)



Source: Baccalaureate and Beyond Longitudinal Study (B&B:1993/94, B&B:2000/01, B&B:2007/08, B&B:2015/16). Cumulative debt includes all individual student loans (federal and private, excluding parental loans) ever borrowed for undergraduate education. Loan value is adjusted using the annual Consumer Price Index (CPI-U). The portion of the box plot is defined by two lines at the 25^{th} percentile and 75^{th} percentile with boundaries at the 10^{th} percentile and 90^{th} percentile.

beyond college are in part motivated by non-monetary considerations. We find a post-bachelor degree to be worth an extra $\$12,000$ beyond its monetary return, with such valuation varying substantially across the income distribution. This finding is consistent with the emerging literature on compensating differentials (see Sorkin 2018, Taber and Vejlin 2020). Because of large and heterogeneous non-monetary returns, decisions on further education are more sensitive than housing decisions to initial wealth levels and indebted students are more likely to give up on post-bachelor degrees.

Monetary returns of post-bachelor degrees are nonetheless relevant, because they give access to careers that deliver a higher pay. Controlling for ability and human capital, our model delivers a wage premium of more than 30% for careers accessible only through a post-bachelor degree. This way, distortions in career and education choices due to rising levels of student debt can amplify inequality and reduce social mobility.

The education decision helps understanding the effect of student debt on housing. There are two groups of graduates that are affected by high debt balances. A first group responds with giving up post-bachelor degrees, and thus increase early participation in labor markets. This group tends to enter home ownership relatively early as well. A second group that would have chosen not to pursue further education even in absence of student debt is subject only to a negative wealth effect, and thus demands less housing. The empirical result can be rationalized as the two forces counterbalancing each other. Finally, we notice that part of returns from human capital investment depend on access to long term asset with good returns; absent housing, or when housing is more expensive, investment in human capital decreases as well.

We conclude discussing policy options regarding the design of student loans repayment systems. Until recently, federal student loans were modeled after mortgage loans, with fixed monthly repayments over a pre-determined period of time. This design indues a high repayment burden right after graduation, especially for borrowers with lower earnings. We show that income-based repayment plans are very effective at increasing human capital accumulation and reducing earnings inequality. Despite this, we observe that only 58% of indebted graduates in 2016 were aware of income-based repayment plans. An obvious policy prescription is to simplify and reduce barriers to access to existing income-based plans, consistently with advice from education finance experts summarized in Barr et al. (2019).

2. Related Literature

The empirical evidence on the effects of student debt on post-college earnings points to a positive relationship, at least in the short run. Using a financial aid experiment at NYU Law School, Field (2009) show that law students who were offered loans were more likely to accept jobs in higher paying corporate law rather than public interest law. Using a difference-in-difference approach, Gerald and Smythe (2019) study the impact of student debt on various labor market outcomes (income, hourly wages, and hours worked). They conclude that indebted students have initial higher earnings due to higher work hours rather than higher wage rates.

Based on a natural experiment in an elite university, Rothstein and Rouse (2011) find that student debt causes college graduates to choose jobs with an initial higher salary instead of low-paid "public interest" jobs. Following a similar appraoch, Luo and Mongey (2019) show that the initial high wages of indebted students don't translate into higher welfare, as graduates choose less satisfying jobs to prioritize repayment. These two papers lay the foundations of our empirical identification approach, as described in the following section.

Higher initial earnings may not necessarily lead to higher lifetime earnings if they are not followed by further human capital investment (Becker (1962), Hause (1972) and Mincer (1974)). In this regard, Zhang (2013) find that student debt has a negative effect on graduate school attendance four years after graduating from a public 4-year college. In a similar vein, Chakrabarti et al. (2020) show that increased tuition shocks (absorbed via higher levels of student debt) cause individuals to forgo graduate school enrollment. Finally, Morazzoni (2022) discusses the impact of student loans on entrepreneurship, and concludes that education borrowing is associated with lower likelihood of opening a firm. We contribute to this literature by providing new causal evidence of the long-term effects of student debt on earnings and career choice through graduate school attendance.

Another set of empirical articles have analyzed the role of student loans on first time home ownership. Controlling for multiple factors, Cooper and Wang (2014), Gicheva and Thompson (2015), and Houle and Berger (2015) show that student debt reduces the likelihood of home ownership for young households. Exploiting variations in tuition for public four-year colleges, Bleemer et al. (2020) find that increasing levels of student debt can account for 11 and 35 percent of the decline in young's home ownership over 2007-2015. Using a similar approach, Mezza et al. (2020) estimate that a $1,000 increase in student debt decreased first time home ownership by approximately 1.5 p.p. for public 4-year college graduates who left school between 1997 and 2005. Differently from these analyses, we focus on the impact of student debt only for bachelor's degree recipients[3].

This article also contributes to the quantitative literature that analyzes how initial conditions affect lifetime earnings inequality. Huggett et al. (2011) find that initial conditions, as measured at age 23, determine more than 60% of variation in lifetime utility, the majority determined by initial human capital differences. However, by including frictional labor markets, Griffy (2021) shows that initial wealth also plays a crucial role in determining life cycle inequality. We contribute to this literature by explicitly modelling multiple dimensions of wealth and human capital accumulation, and by presenting a rich description of career choices that rationalizes the large impact of borrowing constraints on long-term labor market outcomes.

Our structural analysis also speaks to the literature that study student loan program design within a heterogeneous model of life-cycle earnings and human capital accumulation. In this framework, Ionescu (2009) find that repayment flexibility increases college enrollment significantly, whereas relaxation of eligibility requirements has little effect on college enrollment or default rates. Ionescu and

[3] For example, in Mezza et al. (2020), only 46% of the sample had no college degree.

Simpson (2016) show that tuition subsides increase aggregate welfare by increasing college investment and reducing default rates in the private market.

In a similar framework, Johnson (2013) find that tuition subsidies provide larger increases in college enrollment than increasing borrowing limits. We contribute to this literature by examining the effects of alternative student loan repayment plans on graduate school enrollment, earnings and home-ownership choices for college graduates.

3. Empirical Analysis

3.1. Baccalaureate and Beyond Longitudinal Study

The Baccalaureate and Beyond Longitudinal Study (B&B) is a survey of students who completed the requirements for a bachelor's degree in a given academic year[4]. The survey is conducted by the National Center for Education Statistics (NCES), within the U.S. Department of Education. The B&B draws its cohorts from the National Postsecondary Student Aid Study (NPSAS), which collects data from large, nationally representative samples of postsecondary students and institutions to examine how students pay for postsecondary education[5].

Hence, the B&B samples are representative of graduating seniors in all majors and colleges[6]. The first cohort was identified in NPSAS:93 and followed up in 1994, 1997, and 2003. The second cohort was identified in NPSAS:00 and followed up in 2001. The third cohort was identified in NPSAS:08 and was followed up in 2009, 2012, and 2018. The last cohort was identified in NPSAS:16 and was followed up in 2017. Our analysis focuses on the B&B:08/18 cohort, given that graduates were followed up to ten years after graduation and college-level financial aid data was not available for years prior to 2000/01. We also analyze the impact of student debt one year after graduation for students that graduated in 2016.

The B&B connects multiple data sources including student interviews, institution records, government databases, and other administrative sources. Hence, the data contain rich information about students' demographic characteristics, family economic background, financial aid and labor market experiences. In the B&B:08/09 survey, respondents were asked to provide the salary for the job at

[4] Eligible students are those who (1) enrolled at a college participating in federal student aid programs, and, (2) completed their requirements for their first bachelor's degree during that year.

[5] See Wine et al. (2019) and Cominole et al. (2020) for more information about the B&B data collection and sample design.

[6] However, B&B samples are not representative of graduates at the college or state level.

which the respondent worked the most hours[7]. In the B&B:08/12 and B&B:08/18 surveys, graduates were asked to report the total salary for their current primary job. If the respondents had more than one current job, then the job with the longest duration of employment and highest number of hours per week was selected as primary job. In addition, the surveys also asked about graduate school enrollment, attainment, and housing status.

Using harmonized college identifiers, we merge the B&B data with college-level data from the Institutional Post-Secondary Database (IPEDS) and College Scorecard, which include annual data on grants, loans and instructional expenditure per student (among many other variables) since 2000/01 academic year. We use these college-level data to construct the instrumental variable for student debt.

3.2. Descriptive Statistics

We restrict the sample to US citizens and residents students who obtained their bachelor's degree between age 21-25. Mostly, this reflects the fact that the age distribution of college graduates in the B&B sample is strongly skewed to the right[8]. Another reason to focus on young graduates is that the relationship between student debt and the outcomes of interest (i.e. graduate school, earnings and home-ownership) is likely to be different for older graduates[9]. In addition, we restrict the sample to students who first-time enrolled in college between 2001-2004 and did not transfer between colleges. This is necessary, as we use as an instrument variation in financial aid at the college-level. In terms of colleges, we exclude private for-profit colleges.

Table A.1 provides the main descriptive statistics for students that graduated in 2008 and 2016. After imposing the above sample restrictions, the sample contains 9,000 and 8,000 graduates for the B&B:08/18 and B&B:16/17 surveys, respectively. In general, students characteristics and their distribution across colleges remain similar in both cohorts. However, the distribution of student debt shifted to the right: 63% (65%) of college graduates were indebted, with an average amount of student debt of $23,422 ($28,225) in 2008 and 2016, respectively.

For those that graduated in 2008 without any debt, their average annual earnings

[7] Graduates that were employed for pay reported their salary at a yearly, monthly, or hourly rate. Yearly salary was calculated for those who reported it at a frequency other than yearly.

[8] Traditional age college graduates (age 21-23) represent 64% of the B&B:16/17 sample and 65% of the B&B:08/18 sample. Figure 13 shows the distribution of age for the B&B:08/18 sample.

[9] In tables not reported here but available on request, we show that reducing/increasing the maximum age in the sample to 23 or 30 yields similar results.

was \$71,529 ten years after graduation. However, indebted graduates experienced 10% lower earnings 10 years after graduation. Graduate school attainment and home-ownership increased substantially over the first ten years after graduating from college, reaching 44% and 64% for non-indebted graduates, respectively. Indebted graduates were less likely to have a graduate degree ten years after graduation, but there were no significant differences in home-ownership. These average differences in outcomes between non-indebted and indebted graduates might not only capture the impact of student debt, but also differences in demographics and other students characteristics. For example, indebted graduates were more likely to be female, less likely to be white, and, more likely to attend a moderately-selective private non-profit university. In the next section, we introduce a reduced-form approach to estimate the effect of student debt on post-college outcomes after controlling for these observable characteristics.

3.3. Empirical Specification

The relationship between student debt and post-college outcomes (employment, graduate school enrollment and attainment, earnings and home-ownership) can be expressed in the following reduced-form equation:

$$Y_{i,j,\tau} = \alpha_j + \beta Debt_{i,j} + \Gamma X_{i,j} + \epsilon_{i,j,\tau} \tag{1}$$

Where $Y_{i,j,\tau}$ is the individual's outcome τ years after graduating from college j, α_j is a vector capturing college characteristics, $Debt_{i,j}$ is the log of the cumulative amount of individual loans borrowed for the undergraduate degree (excluding parental loans), and $X_{i,j}$ is a vector of observable graduates characteristics.

We control for college characteristics (α_j) that are likely to influence both students financial aid and post-college outcomes. In order to capture college quality, we follow Folch (2021) and model post-college outcomes as a function of the logarithm of average instructional expenditure per student and college selectivity. The college selectivity measure is based on the number of applicants and students admitted, and, the 25th/75th percentiles of college entrance test scores (ACT/SAT). In addition, we control for the sector and the region where the institution is located[10].

We include a rich set of student characteristics ($X_{i,j}$), based on relevant variables used by colleges to put together student aid package for an academic year. These are observed and computed by colleges from the FAFSA application form, which is a free online application for financial aid eligibility where students put all their information.

[10] States are classified in 8 categories using the U.S. Bureau of Economic Analysis (BEA) classification.

We include graduates' dependency status[11], whether they enrolled in college in their state of residence, their financial need[12] (and a squared term) and other demographics (age, sex and race/ethnicity). We also add additional controls to capture graduates college performance (GPA and GPA squared) and major field of study (10 categories).

Even with this rich set of college and students characteristics, we might still face the problem of omitted variable or misspecification bias. For example, important characteristics (e.g. ability and actual family contribution) that explain both the amount of student debt and post-college outcomes may not be well measured in Equation 1. This makes $Debt_{i,j}$ a potential endogenous variable, and thus, the OLS estimator of β is likely to be biased.

3.4. **Instrumental Variable: Institutional Grants**

In this section, we show that differences in financial aid availability faced by all students in the same college offer a way to overcome the identification problem. Students usually receive a year-by-year financial aid package that is determined by college financial aid officers, but it is not known in advance at the time of college application. The package includes student loans, scholarships, and, grants from the government and the institution itself. Differently from government grants and loans, institutional grants are funded from net revenues and assets of the institution and they are the major source of financial aid funding, followed by loans.

In order to capture the substitution between institutional grants and student loans, we follow Luo and Mongey (2019) and construct the ratio of the value of total institutional grants issued by the college to the sum of grants and student loans (grant-to-aid henceforth, $Z_{j,t}$)[13]:

$$Z_{j,t} = \left(\frac{inst.grant_{j,t}}{inst.grant_{j,t} + loan_{j,t}}\right)$$

One may still be concerned that grant-to-aid is correlated with unobserved students characteristics (e.g. ability and actual parental contribution) and these characteristics

[11] Students are considered independent if they meet one of the following criteria: age 24 or older, enrolled in a graduate or professional degree, married, orphan or ward of the court, have legal dependents other than a spouse, a veteran of the U.S. Armed Forces, U.S. Armed Forces active duty. Students under 24 who do not meet any of these conditions but are receiving no parental support may also be classified as independent.

[12] Equal to the total student budget minus the federal expected family contribution (EFC). The EFC is calculated according to a formula established by law. Family's income, assets, benefits, family size and the number of family members who will attend college all contribute in determining each student's EFC.

[13] See Section A.1 for more details on IPEDS data and how this variable is constructed.

have a direct impact on students' post baccalaureate decisions. This correlation may arise because students apply and choose colleges based on a bundle of observed college characteristics, which include the cost of college and the amount of institutional grants in their financial offer letter[14].

For this reason, we also include as an instrument changes in grant-to-aid while students are enrolled in college, which are unlikely to be anticipated for students when making the decision of which college to apply and/or enroll. In order to capture these changes in institutional grant availability, we compute the average variation in grant to aid during college enrollment (where t_0^i represents the year when the student first enrolled in college and t_g^i the year she graduated) as follows:

$$
\begin{aligned}
\Delta Z_{i,j} &= \bar{Z}_{i,j} - Z_{i,j,t_0^i} \\
&= \frac{\sum_{t=t_0^i+1}^{t=t_g^i} Z_{j,t}}{t_g^i - t_0^i - 1} - Z_{i,j,t_0^i}
\end{aligned}
$$

Figure 2 shows how grant-to-aid effectively captures the substitution between institutional grants and student debt for both public and private non-profit colleges in a given academic year (2007/08). The figure, in fact, shows that lower grant amounts end up being compensated by higher borrowing almost systematically. For our identification, however, we also need grant-to-aid ratios to change substantially over time, in ways that are not systematically related to current levels of grant availability. Figure 3 shows substantial variation in grant-to-aid from enrollment to graduation year for students that graduated in 2008.

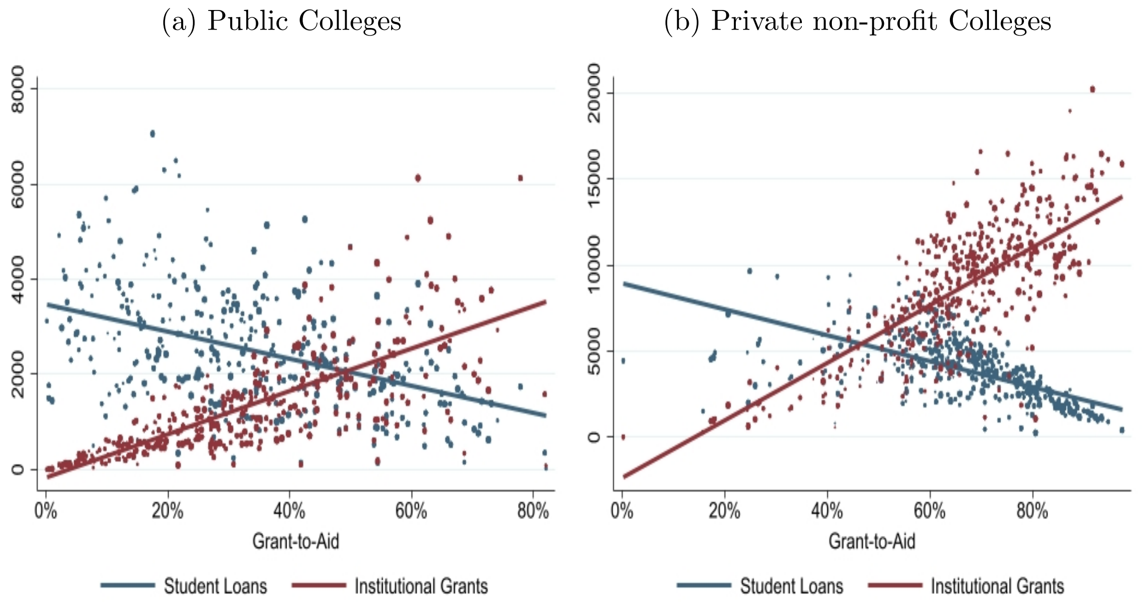
Thus, we model the logarithm of cumulative debt at graduation (first stage regression) as an outcome of individual demand for debt and these supply side changes in grants:

$$
Debt_{i,j} = \mu_j + \delta_1 Z_j + \delta_2 \Delta Z_{i,j} + \Pi X_{i,j} + u_{i,j} \tag{2}
$$

We estimate the model by two-stage least squares regression (for earnings and months employed) and by an instrumental variable Probit model and Bivariate Probit (for graduate school enrollment, attainment, and home ownership). Therefore, it is important that there is significant variation of the instrument with student debt across institutions.

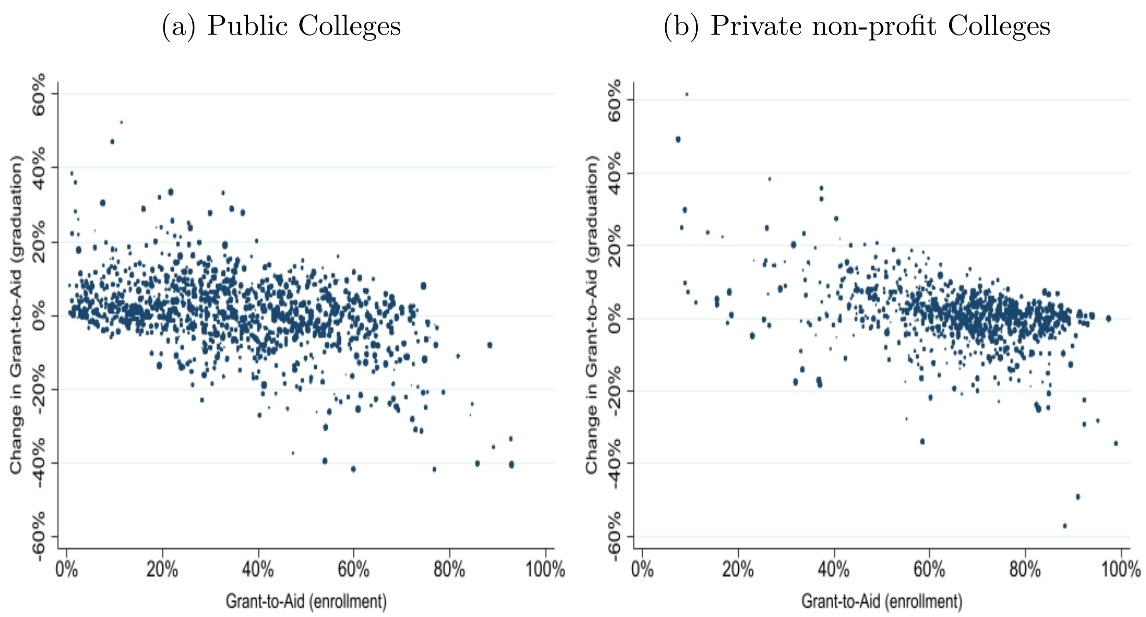
[14] For example, Hoxby and Avery (2014) and Dillon and Smith. (2017) show that low-income students tend to apply to colleges that they appear overqualified. However, Luo and Mongey (2019) provide suggestive evidence that the majority of students do not apply to many schools and then select based on institutional grants: nearly 80 percent of freshmen FAFSA applicants list only one college in their application form, and less than 4 percent list more than five.

Figure 2: Institutional Grants and Student Loans (2007/08)



Source: Integrated Postsecondary Education Data System (IPEDS 2007/08) and Baccalaureate and Beyond Longitudinal Study (B&B:2008/18). Estimates are survey weighted. Blue dots are average student loan balances, red dots are average institutional grant amounts, both at the college level.

Figure 3: Change in Grant-to-aid



Source: Integrated Postsecondary Education Data System (IPEDS 2007/08) and Baccalaureate and Beyond Longitudinal Study (B&B:2008/18). Estimates are survey weighted. Each dot represents a college-specific level of grant-to-aid ratio, Z_j, and how it changes from the first year of enrollment.

Table 1: First Stage Regression

	Debt OLS	Indebted Probit (avg. mg. ef.)
	(1)	(2)
Grant to Aid at Enrollment	-0.35***	-0.099***
	[0.062]	[0.019]
Δ Grant to Aid at Graduation	-0.262***	-0.074**
	[0.099]	[0.031]
F-statistic	21.4	11
Controls	✓	✓
Observations	9,000	9,000

*p<0.1;**p<0.05;***p<0.01

Balanced repeated replication standard errors in brackets.

Source: Integrated Postsecondary Education Data System (IPEDS) and Baccalaureate and Beyond Longitudinal Study (B&B:2008/18). Sample: graduated between age 21 and age 25.

Table 1 shows that the relevance condition is satisfied.[15] For those that graduated in 2008, on average, a 10 percentage points increase in grant to aid at enrollment was correlated with a corresponding 35% decrease in cumulative student debt at graduation. In addition, a decrease in 10 percentage points in grant-to-aid while enrolled in college implied a 26.2% decrease in debt. The coefficients are also statistically and economically significant when estimating a Probit model using as a dependent variable being indebted at graduation.

3.5. The Impact of Student Debt

This section presents our main empirical results. We show the causal effect of debt on post-graduation graduate school enrollment and attainment, home-ownership, earnings, and percent of months employed. We use the estimation strategy proposed in the previous section, that is, exploiting supply-side variations in debt coming from grant availability. Results from the estimation of Equation (1) are given in Table 2. The three columns show the effect of student debt one, four and ten year after undergraduate degree completion in 2008. For each of the five outcome

[15] Table A.2 includes the coefficients for all control variables.

variables, we compare the estimation results from a naive OLS (Probit) regression with the two-stage estimation (2SLS and IV Probit). In addition, for the three dichotomous outcomes, we also show the estimation results from a Bivariate Probit.

Consistent with previous empirical studies, our results show that increasing student debt at graduation leads to an increase in annual earnings one year after graduation. In addition, we show that student debt increases labor supply, as graduates are more likely to be working in the first years post-graduation. However, we find that the positive effect on earnings disappears four years after graduation and reverts to negative ten years later. On average, an increase in student debt by 10% at graduation in 2008 lead to a decrease in annual earnings of $2,7\%$ in 2018.

Reduced form evidence does not offer immediate explanation for this reversal, but there is a smoking gun. Student debt causes a decrease in the likelihood to enroll in post-bachelor degrees, not only in the short-run, but also in the long-run. Most notably, we find that increasing undergraduate student debt balances by 10% causes a decrease in the likelihood of holding a graduate degree by 5% ten years after obtaining the bachelor's degree.

On the other hand, we find no significant delay on first-time home-ownership. The Bivariate Probit estimation shows even a positive effect of debt on first-time home ownership four years after graduation, suggesting non-linearities in the impact of debt on housing. Table 3 displays the effect on home value conditional on entering home ownership, which is significantly negative. This effect suggests that high debt balances still have an effect on wealth accumulation. Given the strong wealth effects observed on other margins, the null impact on the home ownership extensive margin has a less straightforward interpretation. The interaction between career choices and housing investment as a potential channel will be discussed in the structural model section, but Table 4 offers a clue: when we look at college graduates who have not enrolled in any post-bachelor program even ten years after graduation, more indebted students are significantly less likely to enter home ownership. While this result is by no means immune to selection effects, it is consistent with the intuition that, for graduates whose education choices are not impacted by debt balances, student debt is a constraining factor in accessing home ownership.

The results presented in this section are based on a cohort of college students that graduated in 2008. For those that graduated in 2016 (Table A.3), we find that the impact of student debt on graduate school enrollment one year after graduation remained statistically significant, although the initial positive effect on earnings disappears. One could suggest that this effect depends entirely on different business

Table 2: Regression Results (B&B:2008/18)

	t+1	t+4	t+10
	(1)	(2)	(3)
Annual salary:			
OLS	0.012	0.017	-0.011
	[0.017]	[0.01]	[0.014]
2SLS	0.342**	0.045	-0.265**
	[0.154]	[0.106]	[0.122]
Percent of months employed:			
OLS	0.001	0.002	-0.001
	[0.001]	[0.001]	[0.001]
2SLS	0.026**	0.026***	0.008
	[0.012]	[0.009]	[0.008]
Graduate school enrollment:			
Probit	-0.001	-0.001	-0.001
	[0.001]	[0.002]	[0.001]
IV Probit	-0.143***	-0.066***	-0.034*
	[0.027]	[0.021]	[0.019]
Bivariate Probit	-0.314***	-0.380***	-0.285**
	[0.055]	[0.048]	[0.111]
Graduate school attainment:			
Probit	-	-0.001	-0.002
	-	[0.001]	[0.002]
IV Probit	-	-0.037***	-0.051**
	-	[0.014]	[0.022]
Bivariate Probit	-	-0.206***	-0.262***
	-	[0.087]	[0.1]
Home ownership:			
Probit	-	0.003	-0.001
	-	[0.006]	[0.002]
IV Probit	-	-0.002	-0.014
	-	[0.014]	[0.015]
Bivariate Probit	-	0.159	-0.046
	-	[0.110]	[0.193]
Controls	✓	✓	✓
Observations	9,000	9,000	9,000

*p<0.1;**p<0.05;***p<0.01

Balanced repeated replication Delta-method standard errors in brackets.

Source: Baccalaureate and Beyond Longitudinal Study (B&B:2008/18). Sample: bachelor's degree recipients that graduated between age 21 and age 25.

Table 3: Regression Results (B&B:2008/18): Home Values (Home Owners)

	t+4	t+10
	(1)	(2)
OLS	-0.006*	-0.008***
	[0.003]	[0.002]
IV Probit	-0.085*	-0.078*
	[0.047]	[0.04]
Controls	✓	✓
Observations	4,000	5,000

*p<0.1;**p<0.05;***p<0.01

Balanced repeated replication Delta-method standard errors in brackets.

Source: Baccalaureate and Beyond Longitudinal Study (B&B:2008/18). Sample: graduated between age 21 and age 25 and home owners.

Table 4: Regression Results (B&B:2008/18): Housing (Ba Degree Only)

	t+10
OLS	-0.004*
	[0.002]
IV Probit	-0.088*
	[0.049]
Bivariate Probit	-.159*
	[0.093]
Controls	✓
Observations	4,000

*p<0.1;**p<0.05;***p<0.01

Balanced repeated replication Delta-method standard errors in brackets.

Source: Baccalaureate and Beyond Longitudinal Study (B&B:2008/18). Sample: graduated between age 21 and 25 that have not enrolled in post-ba programs as of 2018.

cycle conditions. It is important to point out one important difference in terms of student loan repayment between those that graduated in 2008 and those that graduated in 2016. Since 2012, student loan borrowers have more access to income-driven repayment plans. This could dampen the impact of undergraduate student debt on post-baccalaureate choices and could partly explain the differences across cohorts. We quantitatively explore this channel in section 5.3.

4. The Life-Cycle Model

The life-cycle model described in this section blends the Ben-Porath (1967) human capital model presented in Huggett et al. (2011), extended to include student debt and housing, with a Roy model of career choice (Borjas (1987)), where one career requires an education investment on access. The aim is to build a structural model that not only replicates the intuition of the previous section, but can also be used to perform policy analysis.

4.1. Setting

Agents are economically active at age 23, immediately after graduation. They enter the labor market being heterogeneous in ability (a), human capital (h), liquid wealth (k) and student debt (d), and live for T periods deterministically. During working age, agents can decide to enroll in graduate school: if they do, they access a different career path. Workers also sequentially decide labor and human capital investment within their career, savings and housing and non housing consumption while they pay for student debt (if any).

Preferences. Each agent maximizes expected lifetime utility over non durable consumption (c) and housing services (s) (see Fernández-Villaverde and Krueger (2011), Kaplan et al. (2019), and Boar et al. (2017)):

$$u(c, s) = \frac{c^{1-\sigma}}{1-\sigma} + \frac{s^{1-\sigma}}{1-\sigma} \tag{1}$$

where c>0.

Human Capital. Individuals sequentially choose how many hours to work (l_t) and invest in human capital ($1 - l_t$). Human capital evolves according to the following Ben-Porath law of motion:

$$h_{t+1} = e^{z_{t+1}}(h_t + a((1 - l_t)h_t)^\alpha), \quad z_{t+1} \sim N(\mu_z, \sigma_z^2) \tag{2}$$

which depends on individual's ability (a) and with risk coming from human capital idiosyncratic shocks (z_{t+1}).

Individuals can enroll in graduate school every period. If they do, they attend for S periods. While enrolled, human capital grows in every period at rate γ, and workers pay tuition (p_g) and consume using a combination of their liquid savings (k) and graduate student loans (d_g). Attending graduate school yields utility ξ.

Also, while graduates can switch careers at any point, they would lose the human capital accumulated while working and revert to their initial human capital stock if they do. This friction implies that sorting choices made at the beginning of a worker's career can become hard to reverse as professional experience is accumulated, yielding longer term costs due to permanent under-investment in human capital[16].

Labor Income. When individuals work, hourly earnings are priced competitively to reflect their marginal productivity. Assuming a representative firm that uses human capital from workers in both educational groups, earnings are given by the human capital augmented number of hours worked, multiplied by the equilibrium rental rate (R_j):

$$w_{j,t}(l_t, h_t) = R_j l_t h_t^{\nu_j} \tag{3}$$

where j indicates the educational group the worker is in, $j = \{B, G\}$. Human capital is more productive for workers with graduate school education: $\nu_G > \nu_B$. Therefore, assuming workers in both educational groups make identical human capital investments outside college, differences in earnings would grow as workers accumulate human capital. Workers are also exposed to career-specific unemployment risk: they can be separated from their job with probability p_j; while unemployed, they earn home production b, but cannot invest in human capital. When workers retire, they are assigned pension transfers that are proportional to their lifetime earnings.

The above formulation implies that switching to the career path that follows graduate school has three contrasting effects on human capital investment decisions. First, since earnings in the steeper career path loads more on human capital, investments are riskier. Second, higher marginal product of the existing stock of human capital gives weaker incentives for graduate school educated worker to invest in human capital because of a simple wealth effect. Third, $R_G > R_B$ induces a strong substitution effect, in that every unit of consumption today that is foregone in order to invest in human capital generates higher returns in the future.

Structural estimates of the human capital premium R_G/R_B will inform on whether differences in earnings across career paths are amplified or dampened by endogenous

[16] This choice is appropriate for some post-bachelor degrees, in particular the professional ones, where previous experience is hardly useful in the career implied by the degree. But it is clearly less appropriate to capture the role some other degrees, as MBAs and executive MBAs, play in the career of workers with some years of experience. Executive degrees, however, represent less than 3% of all post-bachelor degrees in the data

human capital investment.

Financial Markets. Agents can save in liquid assets k. Workers are allowed to borrow short term, using the rate r_{-}, but they face a credit card borrowing constraint (ϕ) that depends on their current income. Savings ($k > 0$) yield a constant risk free rate r_{+}.

Student Loans. The traditional and most common option for repaying student loans at the time of our estimates is the 10-year fixed payment plan. Similar to a mortgage, the borrower makes constant payments over 120 months until the balance of principal and interest is paid off. Annual student loan payments (P_d) can be obtained as:

$$P_d = \frac{d_0}{\frac{(1+r_d)^{10}-1}{r_d(1+r_d)^{10}}} \tag{4}$$

where d_0 is the student debt at the time of college graduation and r_d is the gross interest rate on student loans. If a worker enrolls in graduate school, payments are suspended while enrolled and graduate school debt is added to the students' balance. After graduation, undergraduate and graduate student debt are consolidated and a new standard repayment plan is started.

Housing. Workers can buy a house at any moment of their life as long as their life span is long enough that they can cover the 30-year mortgage and they have enough liquid assets to use as a downpayment. Houses vary in size H, and so in price, $P_0(H)$ according to:

$$P(H) = p_0 H^{-\gamma} \tag{5}$$

The parameter γ captures a (constant) elasticity of housing supply, as common in the urban literature (see Hsieh and Moretti (2019)). While we do not formally model equilibrium effects in the housing market, equation (5) represents a reduced form approximation of housing supply. If a worker chooses not to own their house, she has to rent (P_r). The rental price is tied to the average price of a housing unit, $\bar{P}_0$, and is set to match a given price to rent ratio. Individuals can ask for a 30-year fixed mortgage to pay the price of the house (P_o).

At the time of buying the house, individuals face two borrowing constraints: **(1)** they must make a downpayment (1-λ), **(2)** their monthly debt payments (student and mortgage debt) cannot exceed a proportion of their income (ψ). We assume that both constraints must be enforced at origination only. Home owners must always pay the mortgage payment ($P_m(H)$) until mortgage balances are zero, following:

$$P_m(H) = \frac{(1-\lambda)P_0(H)}{\frac{(1+r_m)^{30}-1}{r_d(1+r_m)^{30}}} \tag{6}$$

There is no possibility of default or asking for a second mortgage. Home ownership is treated as an absorbing state, so if an individual is homeowner in a given year, then it will stay as homeowner at all future dates. Homeowners can downsize or upsize their housing investment, but in doing so they face a cost proportional to their owned home's price, τ, that is included to proxy all sorts of frictions (fees, taxes, etc.) faced by owners willing to sell real estate.

Preference shocks. Individuals are subject to career and housing preference shocks, which capture shifts in life events not captured in the model (e.g. household formation or divorce). We model those shifts as taste shocks, i.e. additively separable choice specific random taste shocks, and assume they are i.i.d. Extreme Value type I distributed with scale parameter σ_ε.

4.2. Recursive formulation

We illustrate the problem for agents of different stages of life, as the recursive formulation will differ according to it. The unit of time is a semester. The choice is motivated by several facts: it corresponds to the length of the initial grace period (when student loan payments must not be made), it allows for a reasonable accounting of separation risk (unemployment), and yet it reduces the time dimension enough so that we can solve and estimate the model.

We write future values in recursive expressions by adding a $'$ to them. The choice-specific value functions are denoted indicating the discrete state - for instance, V_H^G indicates the value function of a home-owner with a house of size H and with a post-bachelor degree (G).

4.2.1 Retired workers

At retirement age $t = t_R$, workers are assigned pension transfers (p) that are proportional to their last earnings ($w = w_{t_R-1}$). Retired workers make consumption and saving decisions using their savings from working age (k_{t_R-1}). If they own a home (of size H), they have to pay the residual parts of their mortgage ($m(H)$) in equal payments ($P_m(H)$) until mortgage debt is fully paid off. Otherwise, if they are renters (r), they need to rent and pay P_r every period. Retired workers cannot buy a house, as mortgage duration exceeds their life expectancy. We assume the terminal condition for liquid assets to be equal to zero and thus no bequests. The last two constraints imply that agents are subject to a budget constraint, possibly depending on their current income, and that consumption cannot be negative.

The recursive problem for renters, for $t = t_R, ..., T$, is:

$$V_{r,t}(a, w, k) = \max_{k'} u(c, s) + \beta V_{r,t+1}(a, w, k') \tag{7}$$

$$c + k' + P_r = (1 + r) \cdot k + pw$$

$$m_T = 0, k_T = 0, \ k' \geq \phi(pw), \ c \geq 0,$$

The problem for home owners, with mortgage payment $P_m(H)$ is:

$$V_{H,t}(a, w, k, m) = \max_{k'} u(c, s) + \beta V_{H,t+1}(a, w, k', m') \tag{8}$$

$$c + k' + P_m(H) = (1 + r) \cdot k + pw$$

$$m' = (1 + r_d)m - P_m(H) \geq 0$$

$$k_T = 0, \ k' \geq \phi(pw), \ c \geq 0$$

4.2.2 Workers

Agents enter working age ($t = 1, ..., t_{R-1}$), and face two discrete choices every period: whether to enroll in graduate school ($j = \{B, G\}$), and whether to buy a house or not ($\mathcal{H} = \{r, H\}$). In every period, workers are subject to preference shocks (ϵ) that are i.i.d. Extreme Value type I distributed with scale parameter σ_ε (McFadden (1973)). Workers' problem also entails saving (k) and choosing how much hours to work (l) and invest in further human capital ($1 - l$) in every period. Hence, the dynamic program contains both continuous and discrete choices as in Iskhakov et al. (2017).

For notational convenience, we collect human capital, unemployment and preference shocks in $e = \{z, u, \epsilon\}$, and all the other idiosyncratic states in $x = \{a, h, k, d, m\}$, where d and m indicates student debt and mortgage balances. The recursive problem for renters without graduate school education, while employed[17], is thus:

$$V^B_{r,t}(x, e) = \max_{k',l} \left\{ u(c, s) + \sigma\epsilon_{B,r} + \beta\mathbb{E}[\tilde{V}^B_{r,t+1}(x', e')] \right\} \tag{9}$$

[17] See Appendix A.3 for details about how we compute this problem.

$$c + k' + (P_r + P_d) = (1 + r) \cdot k + w_B(l, h)$$

$$h' = e^{z'}(h + a((1 - l)h)^{\alpha})$$

$$d' = (1 + r_d)d - P_d \geq 0$$

$$k' \geq \phi, \;\; c \geq 0$$

where:

$$\mathbb{E}[\tilde{V}^B_{r,t+1}(x', e')] = \mathbb{E}\left[\max\left\{V^B_{r,t+1}, V^G_{r,t+1}, V^B_{H,t+1} + \sigma\epsilon'_{B,H}, V^G_{H,t+1} + \sigma\epsilon'_{G,H}\right\}\right]$$

and where constraints are the usual dynamic budget constraint, the law of motion of human capital, the law of motion of student debt, and the usual borrowing constraint

Home owners with housing payment $P_m(H)$ face the following problem:

$$V^B_{H,t}(x, e) = \max_{k', l}\left\{u(c, s) + \beta\mathbb{E}[\tilde{V}^B_{H,t+1}(x', e')]\right\} \tag{10}$$

$$c + k' + (P_m(H) + P_d) = (1 + r) \cdot k + w_B(l, h)$$

$$h' = e^{z'}(h + a((1 - l)h)^{\alpha})$$

$$d' = (1 + r_d)d - P_d \geq 0$$

$$m'(H) = (1 + r_m)\, m(H) - P_m(H)$$

$$P_m(H) = \begin{cases} \lambda P_0(H), & \text{at origination} \\ \frac{r_d(1+r_m)^{30}(1-\lambda)P_h(H)}{(1+r_m)^{30}-1} & \text{after origination} \end{cases}$$

$$k' \geq \phi, \;\; c \geq 0, \frac{P_m(H) + P_d}{w_B} \leq \psi$$

where:

$$\mathbb{E}[\tilde{V}^B_{H,t+1}(x', e')] = \mathbb{E}\left[\max_H\left\{V^B_{H,t+1} + \quad \sigma\epsilon'_{B,H}, V^G_{H,t+1} + \quad \sigma\epsilon'_{G,H},\right\}\right]$$

where we added the law of motion of mortgage balances, the equation that determines housing payments, and the loan-to-value constraint. If the worker is in the first period of home ownership, $P_m(H)$ equals to the downpayment required to buy the house. After that period, housing payments are determined by Equation (6).

Defining $\bar{S}$ as the number of periods required to get the degree, the recursive problem of the individual attending graduate school for $s \leq \bar{S}$ is:

$$V_{r,t}^{G}(x, e, s) = \max_{k'} \left\{ u(c, s) + \xi + \beta \mathbb{E}[V_{r,t+1}^{G}(x', e', s')] \right\} \tag{11}$$

$$c + k' + P_r + p_g = (1 + r) \cdot k + d_g$$

$$h' = (1 + g) \cdot h$$

$$d' = (1 + r_d) \cdot d + d_g \cdot 1_{s=1}$$

$$k' \geq 0, \ c \geq 0$$

We assume that, during graduate school, the borrowing constraint with liquid assets is tighter - since the individual is not working she has to keep her liquid assets positive. After graduating, the recursive problem is analogous to Equation (9).

Unemployed workers' problem is analogous, with earnings replaced by b, no human capital investment decision and with a probability to find a job of $1 - p_j$.

4.3. Calibration

We set parameters for the model in two ways. First, we externally calibrate some parameters using estimates that are common in the literature literature or by estimating them independently (Table A.4). The remaining parameters are obtained via structural estimation, using the simulated method of moments (SMM) routine described below.

4.3.1. External Parameters

Timing. Each period time in the model represents two quarters. Individuals start making decisions when they graduate from college. After finishing college, they start working and repaying their student debt. Agents retire at the age of 65 and die when they are 80.

Preferences. Preferences are set using standard calibration in the literature. The yearly discount factor is set to be 0.99. We set the constant relative risk aversion in the utility function to 2.

Earnings and Labor Market Dynamics. Home production b is calibrated to match the Federal poverty threshold for an individual living alone in 2008 ($991 USD a month). The transition to unemployment probability for bachelor holders is set to

5.5% and to 4.5% for post-bachelor degree holders, matching the average number of employment to unemployment transition of the two groups (see Menzio et al. (2016)). Following Cocco (2005), pension payments are set to be 93 percent of the last earned income.

Financial Markets and student debt. The annual interest rate for student loans and the 30-year fixed rate mortgage is calibrated to the 2004-2008 average rate of 6 percent. The risk free interest rate for savings is set at 0 following null real returns after 2008 and credit card borrowing rate is fixed at an annual 11 percent. We set a credit card borrowing limit of $-\$5,000$, targeting a median rate of credit limit to annual labor income for college graduates of 20 percent.

Housing. We set the rental rate to a yearly rate of 5% of the house price. The parameters that determine the loan-to-value (LTV) and DTI are chosen to match institutional features of the US mortgage market. For the LTV parameter, we fix a downpayment ratio of 0.2, impliying a LTV of 80%. This does not fully capture the distribution of the LTV in Freddie Mac data, which has two masses point around 80% and 90%, but accounts for the fact that the first mass point is typically populated by younger first-time buyers and thus seems more appropriate for pinning down the problem of first home ownership (see Greenwald (2018))). In order to qualify for a Qualified Mortgage under CFPB guidelines, a borrower's total debt to income ratio, including the mortgage payment and all other recurring debt payments, cannot exceed 43 percent.

4.3.2. Distribution of Initial Characteristics

In order to simulate the model, we have to make parameter choices regarding starting values of liquid assets, ability, human capital and student debt.

While college graduates typically do not have substantial wealth of their own, they may have access to alternative sources of wealth that are not directly measured. We assume students leave college with zero liquid assets, but receive an exogenous transfer from their parents. We use the Expected Family Contribution (EFC)[18], with an average transfer of $\$16,344$ (μ_k) and a standard deviation of $\$17,455$ (σ_k).

Using the B&B data, we impose an average debt balance of $\$14,738$. This figure is composed by a percentage of 63% of borrowers, with cumulative average balances of \$23,422 (μ_d) and a standard deviation of $18,439$ (σ_d). We also get the correlation between parental transfers and student debt to be -0.15 ($\rho_{k,d}$).

[18] The EFC is calculated according to a formula established by law. Student's family's income, assets, and benefits (such as unemployment or Social Security) are considered in the formula.

Following Huggett et al. (2011) and Athreya et al. (2019), we assume that the distribution of ability and human capital is jointly log normally distributed. We calibrate the initial mean (μ_h) and standard deviation (σ_h) of human capital to match the mean and standard deviation of earnings for employed workers one year after graduation from the B&B:08/09 survey - respectively at $\$31,850$ and $\$17,605$. We take the correlation between human capital and ability ($\sigma_{a,h}$) from Athreya et al. (2019), who estimate a life cycle model of education choice and report a correlation of 0.67.

Finally, we need to determine the correlation between ability and student debt ($\rho_{a,d}$). This parameter has an important interpretation because, if correctly identified, it informs about the bias that an econometrician would be subject to when estimating Equation (1) via OLS. We estimate this parameter, jointly with other structural parameters, to match the key properties of the earnings and home ownership profiles.

4.3.3. Simulated Method of Moments

Structural parameters Θ are jointly determined by Simulated Method of Moments (see Gourieroux et al. (1993) , Smith Jr (1993) and Gallant and Tauchen (1996)). Let x_i be an i.i.d. data vector, $i = 1, ..., n$, and $y_{is}(\Theta)$ be an i.i.d. simulated vector from simulation s, so that $i = 1, ..., N$, and $s = 1, ..., S$. The goal is to obtain Θ by matching a set of simulated moments, denoted as $h(y_{i,s}(\Theta))$, with the corresponding set of actual data moments, denoted as $h(x_i)$. Define:

$$g_n(\Theta) = \frac{1}{n}\left[\sum_{i=1}^{n} h(x_i) - \frac{1}{S} h(y_{i,s}(\Theta))\right] \tag{12}$$

Building $g_n(\Theta)$ in this case faces an important challenge. In classic SMM estimation, exploration of the state space requires the model to be solved enough times to map the error function accurately. In the case of a model with a large state space like ours, this could be very computationally expensive[19]. In addition, there is little certainty that the obtained solution is anything more than a local optima, making estimates less reliable and too dependent on initial values.

To overcome the curse of dimensionality while searching for parameters globally, we discretize the parameter space using sparse grids (see Bungartz and Griebel (2004)). A similar approach in structural modelling has been using in the context of maximum likelihood estimation, see for instance Heiss and Winschel (2008).

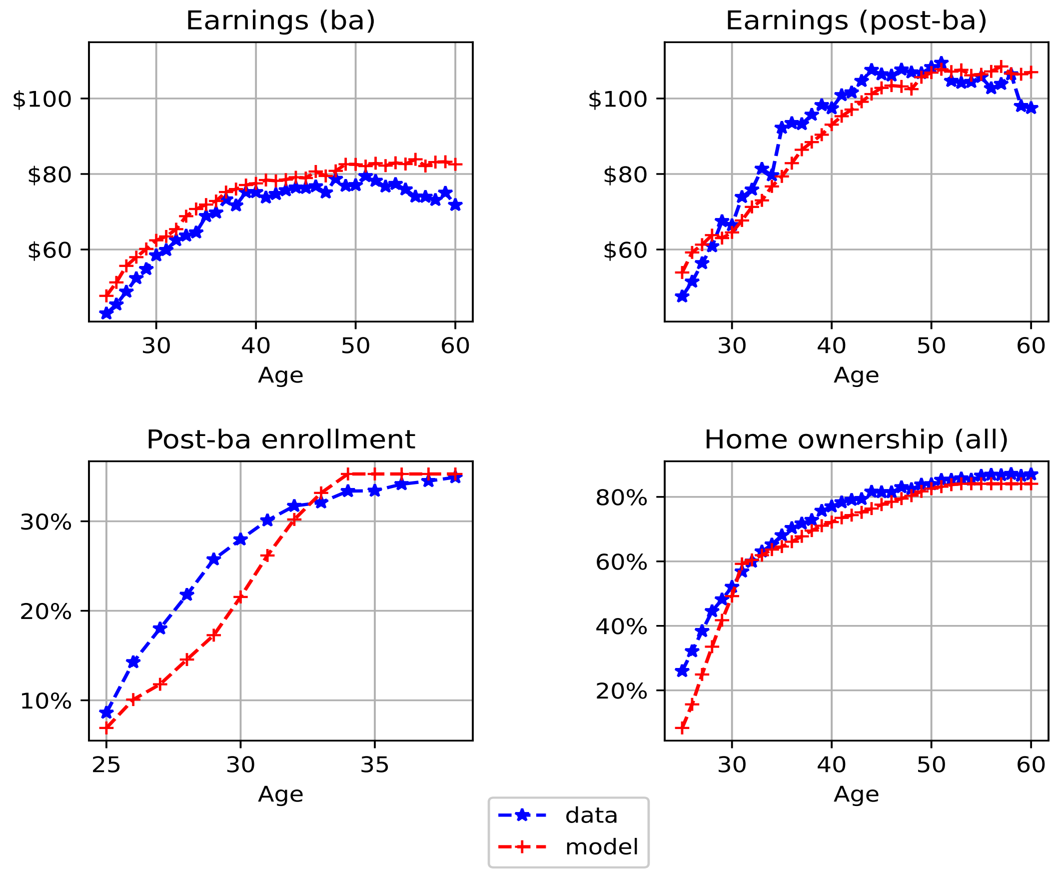
[19] Using a HPC cluster our proposed approach still takes some days to perform a global estimation.

Finding a solution the problem of minimizing weighted squared errors in (12) still faces the issue of the possible presence of many local minima. To make sure our solution is robust, we restart our optimization routine on the estimated error function using multiple sets of starting values. Each routine solves its problem using a Nelder-Mead algorithm. For robustness, we also estimate the model by Basin-Hopping minimization routine, with starting value given by the point in the sparse grid with the lowest error $g_n(\Theta)$.

4.3.4. **Model Fit and Discussion**

Figure 4 compares the model-generated life cycle profiles for earnings, enrollment in post-ba degrees, and home ownership with their data counterparts. The model replicates well overall earnings dynamics and earning dynamics by education subgroups. The pattern in enrollment replicates gradual entry into post graduate studies, with slightly more than a third of college educated workers pursuing further education during their active years.

Figure 4: Life Cycle Profiles (model and data)



Source: Current Population Survey (CPS), model estimates. USD amounts are in thousands.

The model generates a large number of moments that can be used for estimation. Since interactions between intertemporal choices in the model are quite complex, global identification is not possible even if one can attempt a one to one mapping between model parameters and empirical moments. Local identification, however, simply requires that the gradient of the model implied moments with respect to the parameter vector, $\partial h(y_{i,s}(\Theta))/\partial\Theta$, has full rank (Bazdresch et al. (2017)). This condition suggests that for a parameter to be identified, some subset of the vector of implied moments, must change when that particular parameter moves.

Table 5 shows the empirical moments we target in our estimation. Because our underlying motivation is to understand the drivers of career and wealth accumulation choices, we match life cycle earnings and home ownership profiles. We also add moments that tie workers' asset position to their earnings at specific points in time.

Housing parameters are identified mainly by life cycle profile moments - the level being more responsive to changes in value of housing service s, and the slope varying mostly with changes in rental prices (and home prices in general). Finally, the amenity value of graduate school is primarily identified by enrollment levels, with the early enrollment numbers driven mostly by the human capital gain from attending a post-bachelor degree, η_G: a higher value decreases the penalty from attending late, keeping everything else constant, because it allows graduates to recover part of the human capital level lost in the career switch.

Table 6 displays internal parameter values. The amenity value of graduate school is expressed in dollar terms, but does not correspond to ξ. We instead use ξ and then compute the amount of consumption increase that would yield equivalent flow utility to grad school attendance and the value of the human capital intensive career graduate school gives access to. Similarly, we compute the value of housing service by calculating the average reduction in house prices that would produce the same home ownership profile were all agents to value $s = 0$. While average amenity values look small in a life - cycle perspective, there is substantial heterogeneity in how graduates value these two choices.

The left panel in Figure 5 shows the heterogeneity in graduate school attendance valuations, an exercise in the spirit of Athreya et al. (2019). Differences in the consumption - equivalent amount of ξ for low and high levels of disposable income explain the large impact of debt on education: while monetary considerations are almost the only elements poorer workers will consider in evaluating the returns to higher education, the picture for richer individuals is different. Graduates in the right tail of the income distribution plotted in the right panel of Figure 5 will

Table 5: Target Moments

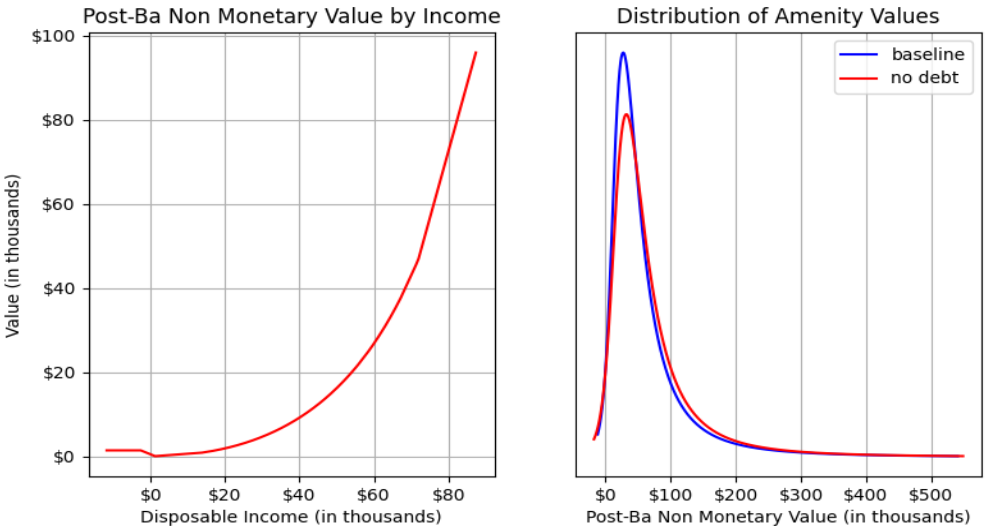
Moments	Mean	
	Data	Model
A. Sample Means		
Post-ba to ba home ownership at age 38[a]	1.0	1.17
Case-Shiller Index, 10 years post-ba[b]	3.57	2.67
Average Home Price, ba holders[b]	$\$270,000$	$\$268,000$
Average Wage Growth, ba holders[c]	2.3%	2.2%
Earnings log-variance, ba holders[d]	0.43	0.43
Completion of post-ba degree[a](age25)	9%	8%
Completion of post-ba degree[a](age30)	27%	22%
Completion of post-ba degree[a](age35)	35%	35%
B. Regression Coefficients		
Home ownership, constant[a]	0.33	0.32
Home ownership, slope[a]	0.04	0.044
Home ownership, curvature[a]	-0.001	-0.001
Post-ba to ba earnings ratio[a], constant	1.10	1.06
Post-ba to ba earnings ratio[a], slope	1.71	1.82

Sources: (a): Current Population Survey (individuals with at least a bachelor degree), (b): Baccalaureate & Beyond (B&B:2008/18), (c): life cycle wage profile for college graduates in Lagakos et al. (2018), and model estimates. (d): log variance of earnings from Meghir and Pistaferri (2004), and model estimates

consider the switch in career choice worth the equivalent hundreds of thousands of dollars in terms of lifetime income. The right panel also tells us how debt balances affect this distribution, by shifting it dramatically to the left, especially for relatively less wealthy individuals.

The mean value for the ability parameter in the Ben-Porath production function is primarily identified by the average wage growth. Since wage growth depends primarily on human capital accumulation, the parameter a is the key driver of its production technology and drives wage growth. Similarly, the log-variance of earnings helps discipline the riskiness of the human capital accumulation process, σ_h. The income parameters are directly linked to their moment counterpart. The skill premium ν_G is largely identified by the ratio of earnings across education groups, and the selection effect by the ratio between the slopes of earnings. Because debt depresses enrollment in post-ba degrees, a more negative value of $\rho_{a,d}$ implies a stronger divergence between the two income paths. The parameter $\rho_{a,d}$ has an important role in linking our

Figure 5: Non Monetary Value of Post Ba Enrollment



Source: Model estimates. Distribution of disposable income for ba graduates aged 25

empirical results to the model. Since $\rho_{a,d} < 0$, we have a clear indication of the direction of the bias in OLS results. Interestingly, it suggests that some negative sorting (in ability or opportunities in the workplace other than continuing towards graduate studies) is biasing our OLS estimates. While job opportunities are identical for agents in our model, we can control for ability explicitly.

While we abstract from explicit parental status in the model, and only include parental transfers as a feature of the starting distribution, these estimates can be useful to think of the ways in which student borrowing could prevent social mobility. The interaction dynamics between starting wealth, large amenity values and monetary returns in our model is consistent with Boar and Lashkari (2021), who show that young Americans from wealthier families sort into professions with higher amenity values, and with Luo and Mongey (2019), who argue that indebted graduates give up on amenities in order to repay debt after graduation.

Our model shows that non-monetary returns and the present value of monetary returns are positively correlated. Indebted graduates, when they give up graduate school, are losing on the monetary side too, because they are front-loading their earnings profile.

Table 6: Internal Parameters

Parameter	Description	Value	Interpretation
	Graduate School Parameters		
ξ	Lifetime amenity value, post-ba	14.90	$\$11,952^*$
γ	Growth in Human Capital	1.47	11.6%
ν_G	Skill Premium	0.31	-
$\rho_{a,d}$	Correlation (ability, debt)	-0.16	-
	Housing Parameters		
s	Housing Service	5.71	$\$1,804^*$
P_0	House Price	11.2	$\$1,353$ monthly rent
P_σ	House Price Dispersion	0.30	$\$98,121$
	Ben Porath Parameters		
α	Production Elasticity	0.16	-
a	Ability, Mean	0.205	-
a	Ability, Standard Dev.	0.03	-
σ_h	Human Capital Risk	0.145	-

Source: Model estimates using Simulated Method of Moments. $*$: these values are computed as the average across the cross sectional distribution of individuals.

5. Model Results

5.1. The Impact of Student Debt

Empirical evidence in section 3.5 highlighted the impact of student debt on earnings and career choices, pointing to a front-loading in earnings, lower earnings growth, and lower graduate school enrollment/attainment. Because the model allows us to explicitly control for ability, we could run the ideal specification in (1) on simulated data as a validation exercise. Table 7 displays the model estimated impact of an increase in debt on earnings, education and housing and compares it with our empirical estimates. In the model, indebted graduates have 0.07% higher earnings for each 1% of additional student borrowing one year after graduation, but 0.196% lower earnings ten years later. The model also replicates qualitatively well the impact of debt on graduate school attendance and home ownership.

The model, at this point, can be used to draw longer term conclusions on the impact of debt-financing for education and more in general on the impact of having low net wealth at the beginning of one's career. The first order effect of being asset-poor is to reduce human capital investments, because of an intertemporal substitution induced by the rigid payment schedule of US college debt plans. There are two main trade-offs involved in the initial career choice. First, workers that not

Table 7: The Impact of Student Debt

Moments	Data	Model
Earnings		
$\partial y_{t+1}/\partial d_t$	0.342**	0.094***
$\partial y_{t+4}/\partial d_t$	0.045	0.11***
$\partial y_{t+10}/\partial d_t$	-0.265**	-0.174**
Graduate School Attainment		
$\partial P(G)_{t+4}/\partial d_t$	-0.066***	-0.039***
$\partial P(G)_{t+10}/\partial d_t$	-0.034***	-0.22***
home ownership		
$\partial P(H)_{t+4}/\partial d_t$	0.002	-0.19***
$\partial P(H)_{t+10}/\partial d_t$	-0.014	-0.05

*: p<0.1;**: p<0.05;***: p<0.01

Source: Empirical results from Section 2 for empirical results, model estimates.

pursue additional education start with higher disposable income, even at the expense of lower income growth compared to the more human capital intensive careers. Attending school allows to postpone payments, but new debt is added to the existing one. Adding the burden of additional borrowing has compounding effects which put considerable pressure on future disposable consumption, thus discouraging enrollment. On the other hand, workers still have the possibility of starting to repay, while working, and then enrolling when their debt burden has reduced. Second, human capital accumulation is a risky investment. While choosing to attend a post-bachelors degree has large returns on average, our estimates of σ_H point to high uncertainty about lifetime income prospects for graduates investing in their skills. This risk is a heavier burden for those graduates who will leave graduate school with large (and compounding) debt balances. Workers whose undergraduate borrowing is above the average level will then start with higher earnings, in part because they are most likely to be working rather than being enrolled. This allows them to build saving buffers that make meeting loan payments easier. After some years, the sorting effects affects earnings, eventually creating a wide and persistent earnings gap.

Heterogeneity in the on-the-job learning ability a is useful not only to match the data. Through the model, we can immediately understand the impact of student debt on career sorting. Sorting matters because it determines a different distributional impact on private life choices, but also and more generally because the higher returns

Table 8: Sorting into Post-Bachelor Degrees

Graduate School Enrollment	Debt Balances		
	Low	Medium	High
Post - Ba Degree Enrollment, up to age 26			
Low Ability	50.43%	2.14%	11.81%
High Ability	51.59%	24.09%	14.68%
Post - Ba Degree Enrollment, up to age 35			
Low Ability	73.91%	24.83%	14.96%
High Ability	75.16%	57.02%	18.88%

Source: Model estimates.

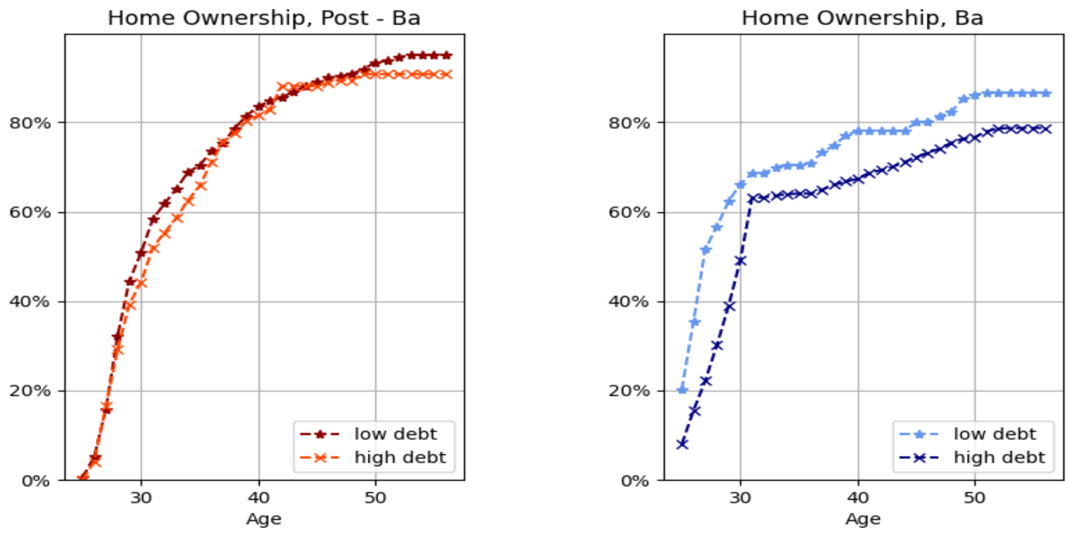
associated with investment in higher education have obvious external benefits for the rest of the economy - see Acabbi et al. (2022). Table 8 shows how ability and debt balances interact to determine career choices. The sorting of low and high debt borrowers is dominated by the effect of debt, but intermediate levels of debt open a wedge in the enrollment decisions. It is somehow surprising, even in a context of severe financial frictions, that net wealth can play such a dramatic role in shaping career decisions. Part of what drives career choices, however, is notoriously related to non-monetary rewards. The model summarizes these motives by allowing a non-negative compensating differential, ξ. Estimates discussed above show ξ to be substantially larger for richer individuals, thus driving the sorting by wealth generated by the model and observed in the data.

5.2. The Role of Housing

While the earnings and career outcomes seem intuitive in isolation, understanding why entry into home ownership is not affected on average by student debt can require a more structured reasoning. An obvious wealth effect is at work, *ceteris paribus* lowering the ability of young graduates to meet the downpayment constraint. Figure 6 helps clarifying the forces at play. As we see in the two panels, more indebted graduates do postpone home ownership, conditional on education choices. However, the housing purchases of post-ba degree holders happen later, highlighting the second channel. The wealth effect of skill investment postpones home ownership - and since student debt primarily depresses investment in human capital, by this channel it increases demand for housing.

Notice this second channel is dampened in the analysis of Mezza et al. (2020), who

Figure 6: Home ownership Profiles by Education



Source: Model estimates.

consider not only undergraduate loans, but take total loan amounts. By lumping together bachelor and post-ba borrowing, they account for the wealth effects for two different pools of workers: those who enrolled in graduate school, and those who have not (yet). In our empirical analysis, and according to our model, the two effects cancel out, at least in the medium horizon.

Having established that career choices can shape the life cycle profile of home ownership, we now study the role of housing in shaping the income and enrollment profiles of graduates. Figure 7 displays how agents in our model would respond to a growth in the average house price index, P_0. As expected, rising home prices reduce home ownership. However, our model predicts small reactions in housing demand. By contrast, the fall in enrollment (especially of low ability individuals) is quite pronounced. Hence, the impact is concentrated on the dimensions of wealth accumulation and in the acquiring of further education from individuals motivated predominantly by non-monetary considerations. The response of income is not obvious ex-ante. Because increasing home prices translate in higher rents, all individuals are poorer when they start working since everyone is assumed to graduate without owning any real estate. The income effect could, in principle, trigger a response in terms of higher human capital accumulation, or increased post-bachelor enrollment by individuals with higher ability. However, higher housing prices also imply a different distribution on returns on housing investments. As we know from Table 7, the main reason for house purchases is the investment motive. Housing, in this model, constitutes the only long-term asset that households have access to in order to transfer significant amounts of wealth into old age.

Average returns from this strategy are thus lower. In this context, delaying entry into labor markets to enjoy the amenity value of further education becomes a riskier and thus less attractive choice. However, since additional education does provide access to higher - paying jobs ($v_G > 0$), the gap in enrollment eventually results in lower earnings. To evaluate the role of housing as a long term asset, we also simulate the model assuming that workers can only be renters. Absent any long term assets, enrollment rates increase. However, because the monetary rewards from attending post-bachelor degrees is dampened by the absence of a long term asset to invest in, enrollment happens at a later age. As a result, income profiles are very similar - see Figure 14. Taken together, these exercises represent a strong case for considering career and wealth decisions jointly, as modelling separately risks over-weighting the returns of each in order to fit the data.

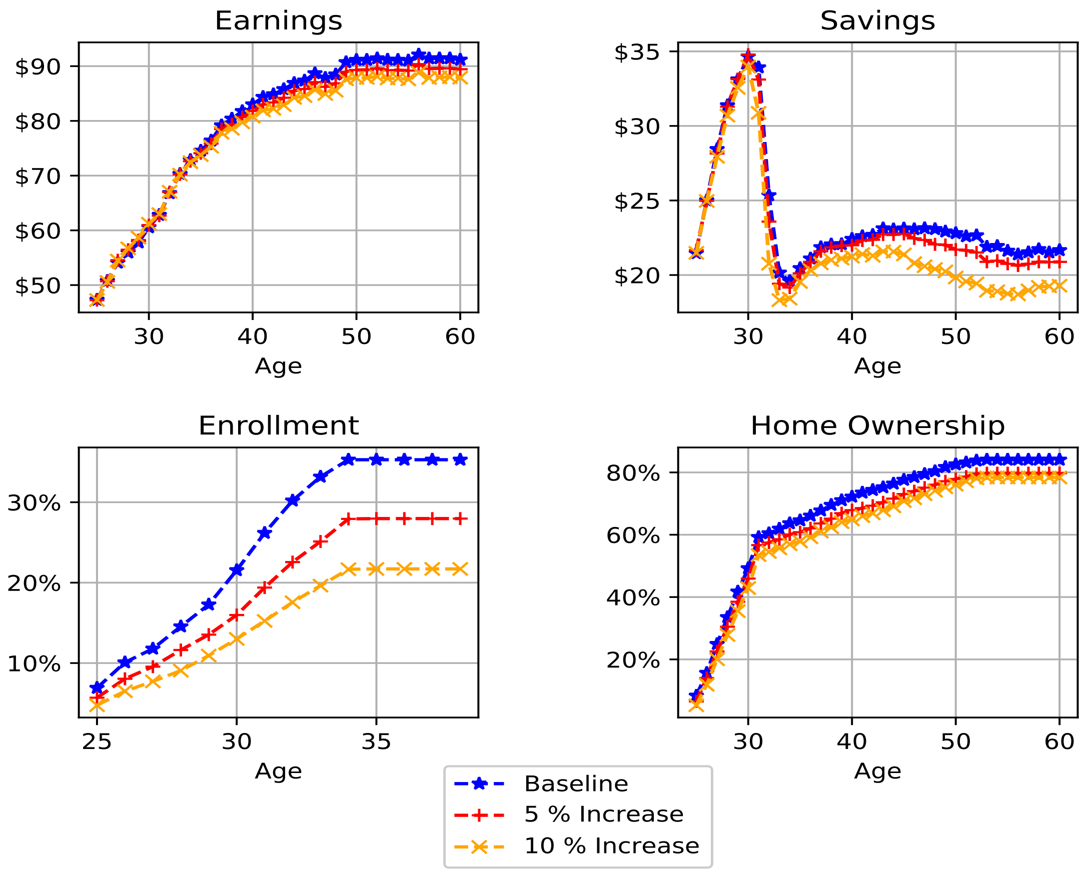
5.3. Income Based Repayment

Income contingent plans have been discussed in economics for a long time. Friedman (1955), in the aftermath of the GI Bill, noticed that conventional mortgage-type loans work well for home loans but not for investment in human capital because of two issues: lack of collateral and asymmetric information. While the first problem implies excessive risk for borrowers, both problems imply excessive risk for lenders. As a result, with conventional mortgage-type loans, there will be underinvestment in human capital.

This applies to all students, but particularly to those from poorer backgrounds who tend to be burdened more heavily by periodical repayments. Plans that link repayment to income are today a popular solution to broadening access to higher education, as countries like Australia and Great Britain made them their baseline program for student finance (see Chapman (2016)). During recent years, changes to old repayment plans and the creation of new ones have expanded generous income-based repayment (or income-contingent loans, ICL) options to a growing number of borrowers in the US. In ideal ICL plans, unlike fixed payment plans, there is no set horizon of loan repayment; instead, the borrower pays a percent of discretionary income each month until the loan is paid off.

A quantitative exercise is necessary to assess the extent to which income based repayment plans moderate the effects of initial student loan debt. On the one hand, enrollment in income driven repayment plans reduces the ratio of student loan payments to monthly wages, increasing disposable income. On the other hand, it can extend the repayment period significantly relative to a 10-year plan, thereby

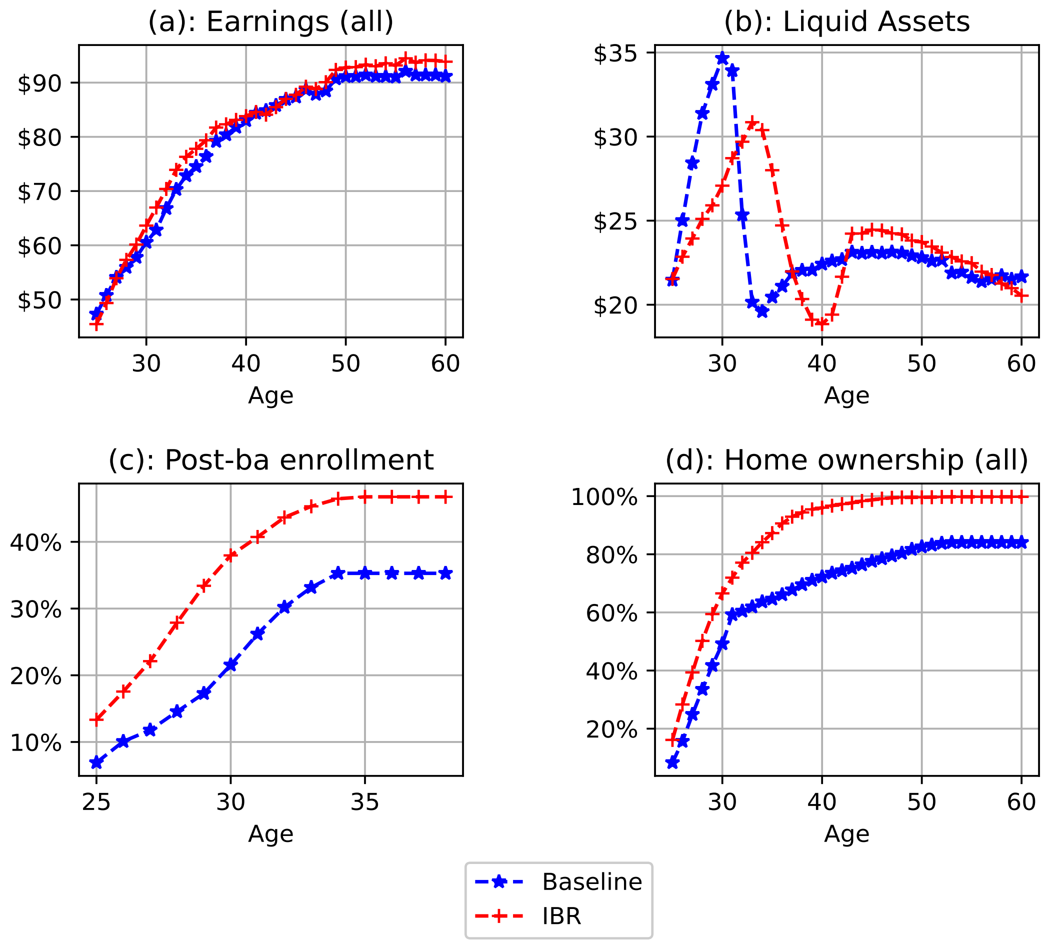
Figure 7: Experiment: Higher House Prices



Source: Model estimates.

potentially increasing the total interest paid by the student loan borrower over the life of the loan.

Figure 8: Baseline vs. Alternative Repayment Plans



Source: Model estimates. Panels (a) and (b): amounts in thousands of $. IBR: PAYE repayment.

In this section, an income repayment plan in every period is introduced in the model as an alternative repayment scheme. The income repayment plan is defined to replicate the *Pay As You Earn Repayment Plan (PAYE)* introduced in 2012. Payments amount to the share of discretionary income, but cannot exceed in any period the amount that the graduate would pay with the installments of a Stafford 10-year plan. The plan goes on for 20 years and at the end of the repayment period, remaining balances are forgiven. The forgiven amount is considered as additional income, to be taxed at the marginal income tax rate. While the PAYE system is far from an ideal ICL, as argued among others by Barr et al. (2019), the current experiment is useful especially to extrapolate current trends, keeping the current legal framework unchanged.

Figure 8 displays the comparative statics between the baseline scenario and one in which all graduates are automatically enrolled in IBR. Both post-bachelor degree enrollment and home ownership increase, with the boost to education dominating in

Table 9: Sorting into Post-Bachelor Degrees (with IBR)

Graduate School Enrollment	Debt Balances		
	Low	Medium	High
Post - Ba Degree Enrollment, up to age 26			
Low Ability	46.96%	38.29%	36.22%
High Ability	43.95%	32.43%	32.17%
Post - Ba Degree Enrollment, up to age 35			
Low Ability	50.43%	58.04%	44.09%
High Ability	45.86%	49.99%	42.66%

Source: Model estimates.

the early years. After age 30, income effects push housing demand and overall home ownership grows compared to baseline. Table 9 shows graduate school enrollment under the income based repayment plan (IBR). We find that enrollment under IBR rises, but at the same time it dampens sorting, because low ability individuals who are more likely to benefit from the built-in forgiveness provision enroll in post-ba more than proportionally in the new scenario. This channel explains the moderate increase in labor earnings shown in panel (a) of Figure 8: from equation (2) we know that the model induces a trade-off between human capital growth and current earnings. Individuals whose learning efforts carry smaller returns might choose to accept lower growth once they access jobs with a large skill premium.

In the standard plan overall balances stay flat for the first ten years, due to a combination of deferment and additional (graduate) debt, then fast deleveraging brings balances to zero by age 45. On the other hand, with IBR initial payments can be lower than the minimum amount required to contain the mechanical growth of balances, spurring a growth that peaks in the mid-30s, as incomes catch up with interest payments. While the program is not guaranteed to be budget neutral, residual balance forgiveness is in part compensated by additional revenue on income and other sources. Considerations on the fiscal implications of different repayment plans go beyond the scope of the present paper.

As shown in this section, linking repayment to income does help alleviating financial constraints. Even if the program did not achieve full participation of graduates, the growth in IBR enrollment can be credited with moderating the impact of the significant growth in undergraduate debt balances occurred between 2008 and 2016. It did, however, contribute to the aggregate statistics showing an acceleration of the growth in debt balances. Our model allows only for a partial equilibrium analysis of the proposed policies. Most of the missing channels would reduce their effectiveness or include elements in the analysis who suffer welfare losses. The need to balance the budget of the forgiveness plan, in particular, implies levying taxes on all workers, including the non-college educated that are not part of our model.

In most cases, endogenous responses of the skill premium might decrease the monetary returns to post-ba enrollment. Human capital externalities, however, could trigger stronger growth and thus increase equilibrium wages of all workers. Analyses of the general equilibrium effects of income-contingent repayment plans have been analyzed in the literature, e.g. by Matsuda and Mazur (2020), who still find them to be welfare-enhancing.

6. Conclusions

What are the implications of higher levels of student debt on college graduates choices? In accordance with previous empirical studies, we find that graduating with higher levels of student debt causes a front-loading of earnings right after college. Nevertheless, we show that higher indebtedness at graduation implies lower earnings growth in the years after graduation. We then argue that this is the result of student debt influencing human capital and career choices of college graduates. In particular, we find that individuals with higher levels of student debt are persistently less likely to enroll in post bachelor degree programs.

At the same time, our empirical analysis finds no effect of student debt on home ownership. We find that this is a result of two opposing forces offsetting each other. While the wealth effect depresses housing purchases, the career effect induces a change in the temporal profile of home ownership that leads to workers having a flatter income profile to advance their purchases.

We also show that large non-monetary returns from career choices play a key role in determining our results. When burdened by high student debt repayments, college graduates become less willing to substitute monetary for non-monetary rewards at the margin. Therefore, as wages of more educated workers back-loaded in time, highly indebted graduates pass on the education investment as it involves many future periods of low consumption. This way, initial differences in wealth, amplified by the large heterogeneity in student debt balances at graduation, compound with unequal access to income growth opportunities. We argue that understanding the role of amenities can shed light on additional ways in which access to economic opportunities can be highly depending on initial endowments.

Several policies have been advocated and implemented to help student loan borrowers. We show that income-based plans (IBR) are an effective policy to reduce career and human capital accumulation distortions induced by student borrowing.

However, only 58% of indebted graduates in 2016 were aware of income-driven student loan repayment plans. Thus, an obvious policy prescription of our paper is to simplify and reduce barriers to access to existing income contingent plans, consistently with advice of education finance experts summarized in Barr et al. (2019).

Future research is needed to understand better the design of student finance and its interactions with wealth accumulation in the context of job polarisation across multiple dimensions: economic returns, amenities, and taking location considerations. In addition, it would be important to extend this analysis including college dropouts and analyze the benefits of alternative repayment plans on easing the ensuing financial burden for this particular group.

APPENDIX

A.1. **IPEDS data**

Using harmonized college identifiers, we merge the B&B student-level data with college-level data from the Institutional Post-Secondary Database (IPEDS). We use the following variables from the IPEDS data center to construct grant-to-aid:

Student Debt:

Average amount of student loans awarded to full-time first-time undergraduates (loan): Any monies that must be repaid to the lending institution for which the student is the designated borrower. Includes all Title IV subsidized and unsubsidized loans and all institutionally- and privately-sponsored loans. Does not include PLUS and other loans made directly to parents.

Percent of full-time first-time undergraduates awarded student loans (ploan): Percentage of full-time, first-time degree/certificate-seeking undergraduate students who were awarded student loans.

Institutional Grants:

Average amount of institutional grant aid awarded to full-time first-time undergraduates (grant): Scholarships and fellowships granted and funded by the institution and/or individual departments within the institution, (i.e., instruction, research, public service) that may contribute indirectly to the enhancement of these programs.

Percent of full-time first-time undergraduates awarded institutional grant aid (pgrant): Percentage of full-time, first-time degree/certificate-seeking undergraduate students who were awarded institutional grants (scholarships/fellowships).

Grant-to-Aid:

We drop colleges with any missing values. We construct $Z_{j,t}$ as follows:

$$\begin{aligned} aid_{j,t} &= (\frac{TotalDebt_{j,t}}{Indebted_{j,t}}) \cdot (\frac{Indebted_{j,t}}{Students_{j,t}}) + (\frac{Grant_{j,t}}{Recipient_{j,t}}) \cdot (\frac{Recipient_{j,t}}{Students_{j,t}}) \\ &= ploan_{j,t} \cdot loan_{j,t} + pgrant_{j,t} \cdot grant_{j,t} \end{aligned}$$

$$Z_{j,t} = \frac{pgrant_{j,t} \cdot grant_{j,t}}{aid_{j,t}}$$

A.2. **Payment Freezes**

Entering the COVID pandemic, the US government introduced and successively extended provisions to pause debt payments in light of potential labor market disruptions. [1] This plan included a suspension of loan payments, a 0% interest rate, and stopped collections on defaulted loans. We briefly study how an unexpected 2-years pause in payments affected early labor market outcomes. We choose to leave other structural features of our model unchanged: contrary to initial expectations, the employment of college graduates rebounded quickly after 2020Q2, making the pause an interesting episode to look at the impacts of temporary liquidity relief.

Figure 9: The Impact of Freezes

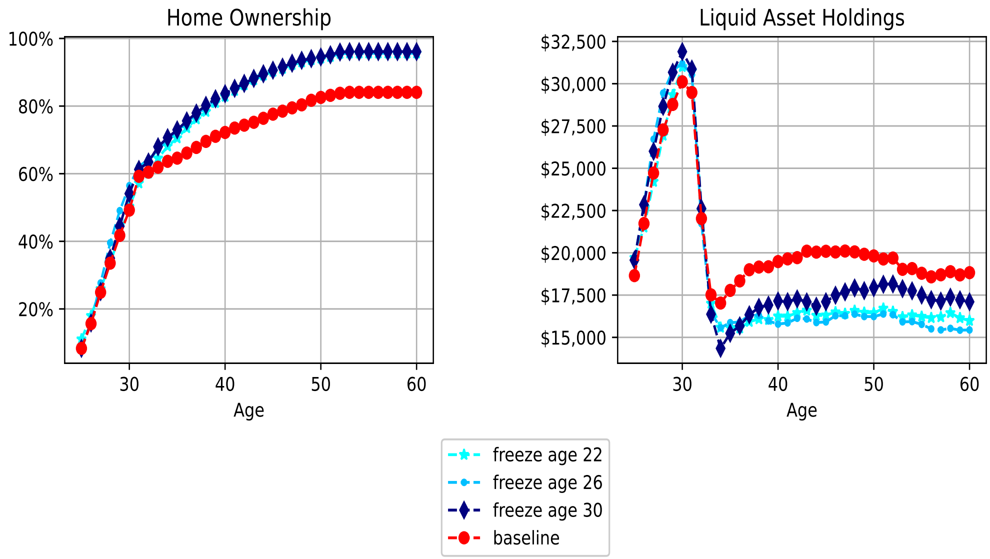
To compute the impact of a 2-year freeze, we simulate the model for 20 age bins, starting at the first period after graduation and ending at the last period before the end of the standard 10-year repayment plan. The effects are then averaged across age groups.

Figure 9 shows the impact of the freeze across age groups. While the impact is differentiated, the aggregate picture already delivers two intuitions. The first is that liquidity constraints matter more for housing. When they are relaxed, housing demand increases, in part at the expense of late enrollment in post-bachelor degree programs. Constraints to education are less impacted because, due to the

[1] As part of the CARES act, a 14-billion-dollar higher education emergency relief fund was created, which included measures on education labeled under *COVID-19 Emergency Relief and Federal Student Aid*.

temporary nature of debt relief, they would bind again once the worker is out of graduate school. The second intuition is that liquidity constraints matter also later in the life of a worker, and not only in the years immediately following graduation: workers use the payment freeze to build saving buffers that allow them to meet downpayment constraints later, with the impact in home ownership visible starting from age 30.

Figure 10: The Impact of Freezes across Age Groups



A.3. **Solution Method**

A.3.1. **Discrete-Continuous Choices**

We illustrate how we take into account discrete choices with the problem of an employed renter with student loans, as in the Bellman Equation (9). For illustrative purposes only, we assume no borrowing constraints. If the worker had no discrete choices to make, the Bellman equation for the optimal consumption of a worker would satisfy the following first order condition known as the Euler equation:

$$0 = u'_c(c, s) - \beta(1 + r)\mathbb{E}\left(u'_c(c', s')\right) \tag{A.1}$$

However, since at any period the renter worker can choose two discrete choices (to become a homeowner or switch career), the problem at the state vector point $\{a, h, j, d, e, t\}$ involves solving for all the possible combinations of available discrete choices.

Following Iskhakov et al. (2017), we assume instead that the discrete choices are affected by choice-specific taste shocks, $\sigma_e \varepsilon_t$, i.i.d. Extreme Value type I distributed with scale parameter σ_ε as in McFadden (1973).

Taking again the value function in (9). Abstracting from career and repayment choice, and focusing only on the home-ownership decision, the expected value of the future value function becomes:

$$\begin{aligned}\mathbb{E}[V'] = \max \mathbb{E}[V_r(k', h', j', m', d', e', t+1)], \mathbb{E}[V_{o,\lambda}(k', h', j', m', d', e', t+1)] =\\ = \max \mathbb{E}[V_r(\cdot, t+1) + \sigma_\varepsilon \varepsilon(o)], \mathbb{E}[V_{o,\lambda}(\cdot, t+1) + \sigma_\varepsilon \varepsilon(r)] =\\ = \sigma_\varepsilon \log\Big(\exp\{V_r(\cdot, t+1)/\sigma_\varepsilon\} + \exp\{V_{o,\lambda}(\cdot, t+1)/\sigma_\varepsilon\}\Big)\end{aligned} \tag{A.2}$$

Thus, the Euler equation for a renter can then be written as:

$$\begin{aligned}0 = u'_c(c, s) - \beta(1 + r)\mathbb{E}\Big[u'_c(c', s' > 1) \cdot P(s' > 1|k', h', j', m', d', e')\\ + u'_c(c', s' = 1) \cdot P(s' = 1|k', h', j', m', d', e')\Big]\end{aligned} \tag{A.3}$$

where $P(s' > 1)$ and $P(s' = 1)$ are conditional choice probabilities given by the binomial logit formula:

$$P(s' > 1|k', h', j', m', d', e') = \frac{\exp\{V_{o,\lambda}(\cdot, t+1)/\sigma_\varepsilon\}}{\exp\{V_{o,\lambda_H}(\cdot, t+1)/\sigma_\varepsilon\} + \exp\{V_r(\cdot, t+1)/\sigma_\varepsilon\}}$$
$$P(s' = 1|k', h', j', m', d', e') = \frac{\exp\{V_r(\cdot, t+1)/\sigma_\varepsilon\}}{\exp\{V_{o,\lambda}(\cdot, t+1)/\sigma_\varepsilon\} + \exp\{V_r(\cdot, t+1)/\sigma_\varepsilon\}} \tag{A.4}$$

A.3.2. **Borrowing constraints**

Solving (9) requires taking care of an additional issue. Formally, given the state S and indicating the Euler equation as $\phi : S \times \mathbb{R}^m \to \mathbb{R}$, and the policy function as $k' : S \times \mathbb{R}^m \to \mathbb{R}$, one needs to find policy and multiplier $(k', \mu) \in \mathbb{R} \times \mathbb{R}$ s.t.

$$\phi(S, k', \mu) = 0 \ , \ k' \geq \phi \perp \mu \geq 0 \tag{A.5}$$

Following Garcia and Zangwill (1981), this problem can be transformed into a system of two equations, and can then be solved using standard solution algorithms for root finding.

Define a variable α such that:

$$\alpha \equiv \begin{cases} \mu, & \text{if } \mu \geq 0,\ k' = \phi \\ -k', & \text{if } \mu = 0,\ k' \geq \phi \end{cases} \tag{A.6}$$

and

$$\begin{aligned} \alpha^+ &= (\max(0, \alpha))^k \\ \alpha^- &= (\max(0, -\alpha))^k \end{aligned} \tag{A.7}$$

where $k \in \mathbb{N}^+$. The variable acts like a "penalty" when the constraint is violated, forcing the algorithm to search in the feasible set. The problem can be rewritten as finding policies and α such that:

$$\phi(S, k', \alpha^+) = 0 \ , \ k' - \alpha^- = 0 \tag{A.8}$$

A.4. **Additional Figures**

Figure 11: Net Cost of College

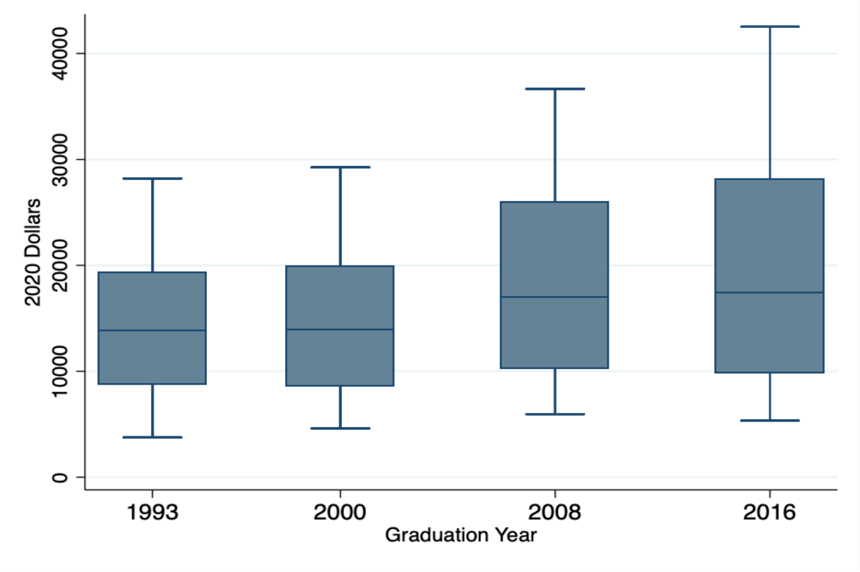
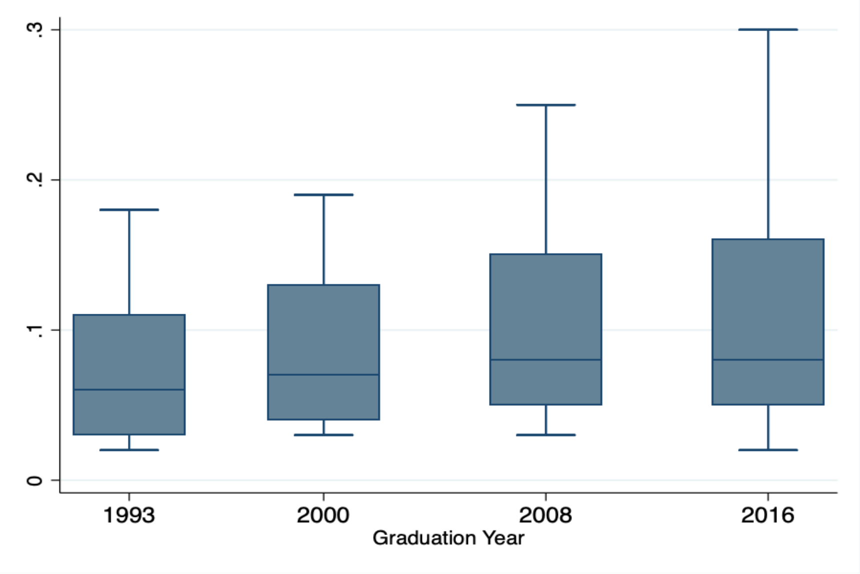
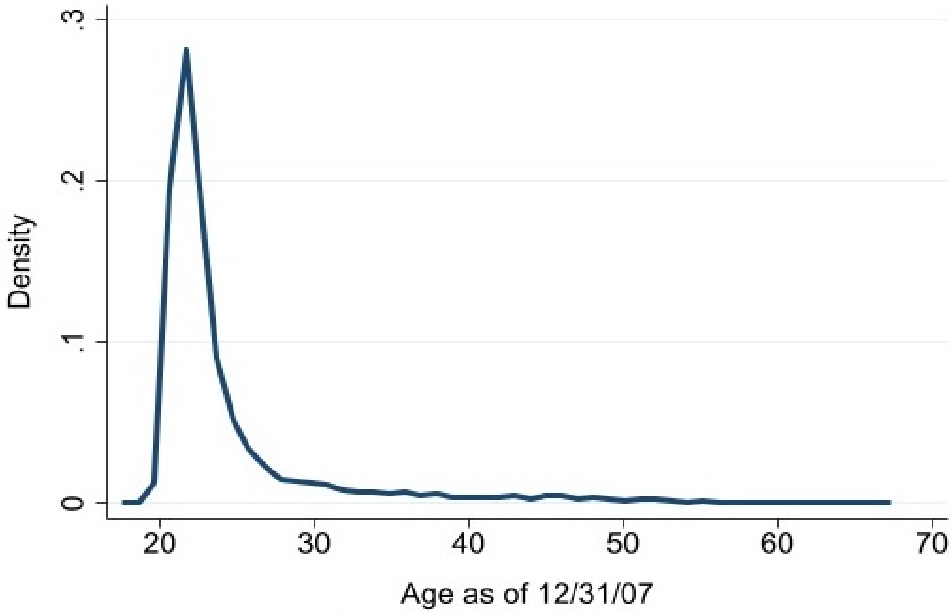


Figure 12: Monthly Student Debt Repayment



Source: Baccalaureate and Beyond Longitudinal Study (B&B:93/94, B&B:2000/01, B&B:2007/08, B&B:2015/16). Figure A1.1 shows student budget minus all grants for graduating senior students and Figure A1.2 shows graduate's monthly student loan payment as a percent of their monthly income.

Figure 13: Age Distribution



Source: Baccalaureate and Beyond Longitudinal Study (B&B:2007/08).

Figure 14: Counterfactual Simulation without Housing

Source: Model Estimates

A.5. **Additional Tables**

Table A.1: Descriptive Statistics

	B&B:08/18		B&B:16/17	
	Not Indebted	Indebted	Not Indebted	Indebted
Undergraduate Student Debt				
Percentage Indebted at Graduation	37%	63%	35%	65%
Avg. Cumulative Student Debt at Graduation (>0)		$ 23,422		$ 28,225
		[18,439]		[18,917]
p25		$ 11,625		$ 16,459
p50		$ 19,875		$ 26,924
p75		$ 29,504		$ 33,920
College Characteristics				
Public 4-year	73%	64%	70%	67%
Moderately Selective	50%	56%	55%	68%
Very Selective	41%	32%	42%	26%
New England	7%	7%	8%	9%
Mideast	15%	20%	18%	20%
Great Lakes	15%	18%	13%	18%
Plains	7%	10%	5%	8%
Southeast	27%	25%	25%	23%
Southwest	9%	8%	8%	8%
Rocky Mountains	6%	3%	4%	3%
Far West	15%	9%	19%	12%
Avg. Expenditure per FTE student (in thousands)	9.69	8.41	14.5	11.1
	[8.98]	[6.48]	[13.9]	[7.5]
Student Characteristics				
Female	54%	59%	53%	58%
White	80%	76%	72%	69%
Dependent	14%	19%	22%	18%
Attending In-state College	24%	17%	28%	23%
Avg. Student Financial Need	$ 7,259	$ 12,168	$ 17,695	$ 18,972
	[9,430]	[11,486]	[18,098]	[17,364]
Avg. GPA at graduation	3.3	3.2	3.4	3.2
	[0.5]	[0.5]	[0.4]	[0.5]
Post-college Outcomes				
Avg. Earnings (t+1)	$ 27,404	$ 26,400	$ 27,994	$ 27,746
	[21,804]	[18,700]	[24,202]	[20,811]
Avg. Earnings (t+4)	$ 42,428	$ 39,732		
	[30,578]	[25,494]		
Avg. Earnings (t+10)	$ 71,529	$ 64,537		
	[61,971]	[52,824]		
Graduate School Attainment (t+1)	3%	2%	2%	2%
Graduate School Attainment (t+4)	26%	23%		
Graduate School Attainment (t+10)	44%	39%		
Home-ownership (t+4)	30%	31%		
Home-ownership (t+10)	64%	62%		
Students Obs.	3,000	6,000	3,000	5,000

Source: Baccalaureate and Beyond Longitudinal Study (B&B:2008/2018 and B&B:2016/2017). Estimates are survey weighted using balanced repeated replication. Sample: Bachelor's degree recipients age 21-25.

Table A.2: First Stage Regression (including all controls)

	Debt Balance OLS (1)	Indebted Probit (2)
Grant to Aid at Enrollment	-0.353***	-0.099***
	[0.063]	[0.019]
Δ Grant to Aid at Graduation	-0.262***	-0..07***
	[0.099]	[0.032]
Public College	-1.729***	-0.474***
	[0.286]	[0.086]
Selective	-0.337	-0.086
	[0.212]	[0.065]
Avg. log Expenditure per FTE student	-0.299	-0.091
	[0.209]	[0.064]
Mideast	0.598	0.184
	[0.415]	[0.136]
Great Lakes	0.558	0.148
	[0.424]	[0.142]
Plains	0.262	0.129
	[0.454]	[0.155]
Southeast	-0.795	-0.190
	[0.416]	[0.138]
Southwest	-0.581	-0.130
	[0.449]	[0.144]
Rocky Mountains	-1.395**	-0.373**
	[0.551]	[0.173]
Far West	-1.319**	-0.353**
	[0.441]	[0.141]
Independent	-0.982***	-0.260**
	[0.324]	[0.103]
Financial Need	1.294***	0.359***
	[0.098]	[0.032]
Financial Need (sq)	-0.168***	-0.044***
	[0.046]	[0.016]
Out-state	-0.952***	-0.291***
	[0.204]	[0.064]
Age 22	0.279	0.073
	[0.197]	[0.061]
Age 23	0.592***	0.144***
	[0.219]	[0.068]
Age 24	1.725***	0.515***
	[0.443]	[0.146]
Age 25	2.195***	0.568***
	[0.576]	[0.2]
Male	-0.482***	0.138***
	[0.167]	[0.051]
Black or African American	1.032***	0.369***
	[0.282]	[0.113]
Hispanic or Latino	-0.495	-0.136
	[0.355]	[0.107]
Asian	-0.227	-0.040
	[0.369]	[0.110]
Other	0.297	0.107
	[0.458]	[0.154]
GPA	-1.288***	-0.349***
	[0.190]	[0.059]
GPA (sq)	-0.866***	-0.236***
	[0.200]	[0.065]
Constant	9.378***	1.265***
	[0.855]	[0.264]
Major of Study (10 categories)	✓	✓
Observations	9,000	9,000

*p<0.1;**p<0.05;***p<0.01

Balanced repeated replication standard errors in brackets.

Source: Integrated Postsecondary Education Data System (IPEDS) and Baccalaureate and Beyond Longitudinal Study (B&B:2008/18). Sample: bachelor's degree recipients that graduated between age 21 and age 25.

Table A.3: Regression Results (B&B:2016/17)

	Graduate School Enrollment	Annual Salary
	(1)	(2)
Probit / OLS	-0.002	0.048***
	[0.001]	[0.013]
IV Probit / 2SLS	-0.055**	-0.017
	[0.026]	[0.216]
Bivariate Probit	-0.195***	-
	[0.065]	-
Controls	✓	✓
Observations	8,000	8,000

*p<0.1;**p<0.05;***p<0.01

Balanced repeated replication Delta-method standard errors in brackets.

Source: Baccalaureate and Beyond Longitudinal Study (B&B:2016/17). Sample: bachelor's degree recipients that graduated between age 21 and age 25.

Table A.4: External Parameters

	Parameter	Value	Description	Source
Preferences				
	T	126	Periods	-
	R	88	Working Periods	-
	β	0.99	Discount Factor	-
	σ	2	Risk Aversion	-
Career				
	p_g	\$ 50,000	Cost of Graduate School	IPEDS
	S	4	Graduate School Periods	NCES
	p	0.93	Income in retirement	Cocco (2005)
	p	$\{5.5\%, 4.5\%\}$	Separation Probability	Menzio et al. (2016)
	b	\$991	Home Production	Federal poverty threshold (2008)
Financial Markets				
	ϕ	$-$\$ 5,000	Credit Card Limit	SCF
	r^+	0%	Interest on liquid assets	FRB (2014)
	r^-	11%	Borrowing Rate	FRB (2014)
	r_d	6%	Interest on mortgages	Department of Education and PMMS
Housing				
	λ	0.2	Downpayment	Greenwald (2018)
	ψ	0.43	Debt-to-Income Ratio	Dodd-Frank limit
	$P_r/\bar{P}_0$	0.05	Price-to-rent	Case-Shiller index (2008-2012)
	τ	10%	Housing Transction Cost	Global Property Guide
	γ	2^{-1}	Housing supply elasticity	Saiz (2010) (average, big+small)
Policy				
	r_{ibr}	10%	Repayment Rate for IBR	Consumer Financial Protection Bureau

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