Go Big or Buy a Home:
Student Debt, Human Capital and Household Formation*

Marc Folch[1] and Luca Mazzone[2]

[1] *University of Pennsylvania*
[2] *University of Zürich and Swiss Finance Institute*

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Abstract. Do financial constraints affect human capital accumulation of young workers? Does student debt play a role in household formation? Using supply side variations in college aid policies, we empirically analyze the impact of student debt on post baccalaureate decisions. We find that student debt induces a front loading of earnings, an anticipation in household formation and has a negative and persistent effect on graduate school attendance. We then introduce and estimate a life cycle model with endogenous human capital accumulation, career choice and housing. Our results highlight the importance of differences in net wealth at labor market entry as determinants of long run human and physical capital accumulation. We also show that housing is fundamental to understand dynamics in career and enrollment choices over the life cycle. Finally, we compare alternative policy proposals. A widespread adoption of an income based repayment plan and a more ambitious forgiveness plan have similar effects, as both increase human capital accumulation, earnings growth, and postpone entry into homeownership.

Keywords: Student Loans, Human Capital, Housing.

JEL codes: I22, E24, J32, J38, R21

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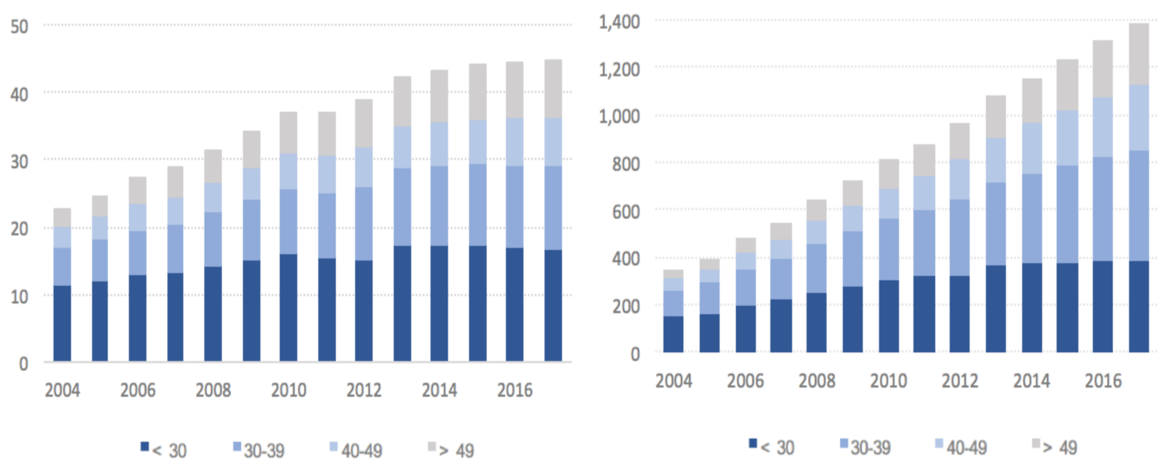
1 Introduction

We study the effects of student debt on career and housing choices of young workers, and introduce a theoretical framework to look at their interaction. Between 2004 and 2018, the outstanding stock of student debt more than tripled in the United States (**Figure 1**). As of December 2018, there were 44 million student loan borrowers who owed \$1.46 trillion in total[1]. Student borrowing is now more likely to be a burden for a higher percentage of college graduates and a relevant factor they take into account in their economic and financial decisions. In the same time period, post bachelor attainment for young workers has almost doubled, while home ownership rate has declined after reaching a peak in the pre crisis years (**Figure 2**).

Figure 1: Trends in Student Debt

(a) Student Loan Borrowers (millions) (b) Student Loan Balances (billions of dollars)



Source: FRBNY Consumer Credit Panel/Equifax

In presence of financial constraints, student debt affects post graduation choices by making further borrowing more difficult. As the relative value of current consumption grows, and workers postpone additional human capital investment, a series of life cycle decisions are consequently affected. We highlight one often overlooked cost of additional investment in human capital, that is the postponing of household formation. When this channel is taken into account, the initial impact of financial constraints on human capital accumulation is amplified, as the relative value of additional human capital investment decreases throughout the life cycle, due to stronger horizon effects induced by mortgage repayment and retirement.

The persistent effects of workers' initial conditions on labor market outcomes have

[1]Most of the increase in student debt has been attributed to the substantial rising cost of college over the last decade (see **Looney and Yannelis (2015)** for a comprehensive account.). Since 2004, tuition at four year colleges increased at an average rate of 3% per year, and student debt surely helped to moderate the impact of higher costs on college enrollment, but more students leave now from college with student debt and borrowers graduate with higher balances.

Figure 2: Post BA Enrollment and Homeownership for BA Graduates

(a) Post BA Attainment (b) Homeownership

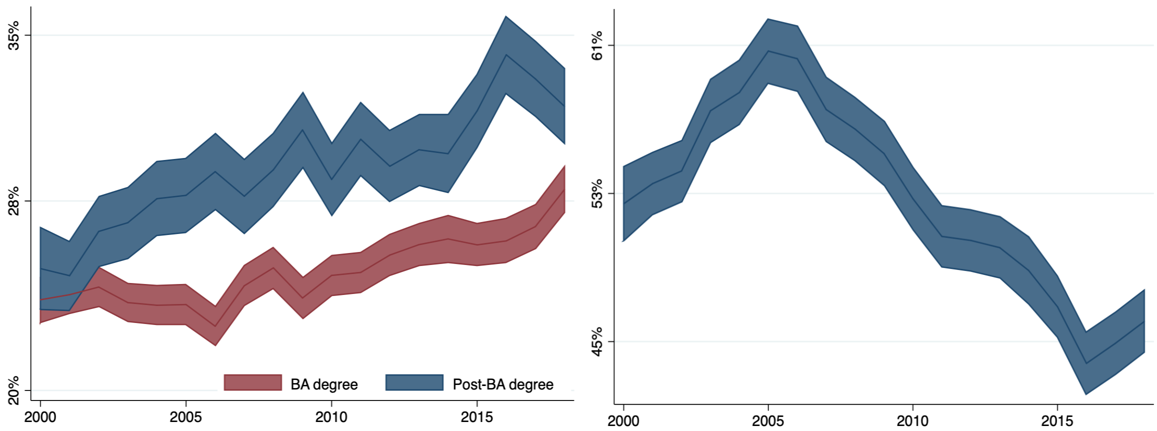


Figure 2a shows the percentage of post BA degree holders (among college graduates) together with the percentage of BA degree holders aged 25-35. Figure 2b plots the home-ownership rate for college graduates aged 25-35. The estimates are computed using a logistic regression on year dummies for the reference person and using ASEC weights. The shaded area indicates the range of the 95% confidence intervals. Source: CPS (2000-2018).

been subject to extensive research. Business cycles have strong effects on long term outcomes for earnings and wealth accumulation of those who start their career from a less favorable position (**Kahn (2010)** and **Oreopoulos, Von Wachter and Heisz (2012)**), while initial wealth is an important determinant of long term wage growth (**Griffy (2019)**). Student debt, being the second largest form of household debt after mortgages, is the most natural choice for understanding the role of financial constraints on young workers.

We use the Baccalaureate and Beyond Longitudinal Study (**B&B**), a restricted access dataset compiled by the National Center for Education Statistics. The **B&B** surveys cover a representative sample of U.S. college graduates interviewed on successive waves, starting in 1991. In order to empirically examine how college borrowing affects career choices, earnings, and wealth accumulation in the years after graduation, we need to overcome notorious identification problems, as the amount borrowed may be determined by unobserved individual ability or different expectations, which in turn would affect all post graduation choices.

We address the identification problem by introducing an instrument based on variations in colleges' financial aid. Composition of aid at the college level is calculated using public access data from the Integrated Postsecondary Education Data System (**IPEDS**) and focusing on institutional grants. Institutional grants, funded from private sources and net assets of the institution, provide supply side financial aid variations faced by all students in a given college but are not directly related to each student's characteristics. Thus, they provide variation in individual's student debt but they are not correlated with post bachelor choices through unobserved characteristics of the borrowers. We also show that, when controlling for appropriate college characteristics, our suggested instrument does not explain any variation in student body characteristics that would suggest applicants sorting into different institutions based on differences in the measure of grant policy we use.

Our results indicate that higher levels of student debt induce a front loading of earnings, while they significantly and persistently deter attendance to post bachelor degree programs, which contributes to lower earnings growth. Indebted graduates earn 0.28% more for each percentage increase in student debt in the first year. Over time, this effect is compensated by wage growth being 0.18% lower. Borrowing also generates an anticipation in home ownership and cohabitation, although more indebted graduates end up buying less expensive homes.

We develop a model with endogenous (risky) human capital accumulation enriched by career choices and housing decisions to rationalize the empirical evidence and understand the importance of life cycle forces in shaping post graduation outcomes. After graduating from college, individuals enter the labor market and are heterogeneous in ability, student debt, human capital and initial liquid wealth. They sequentially decide on human capital investment, savings, non housing and housing consumption while they pay for student debt. At any point, they can enroll in a post bachelor program and, if they do, take on additional student debt. Available careers differ in the way productivity, and thus compensation, is linked to accumulated human capital. Workers with a post bachelor degree gain access to a career path that carries a positive skill premium.

The model is estimated by Simulated Method of Moments using a combination of data from **B&B** and Current Population Survey (**CPS**). Our theoretical framework implies that, because of introducing career heterogeneity and post schooling credit constraints, student debt plays a key role in explaining inequality throughout the life cycle. College graduates with higher student debt sort into careers with lower compensation for human capital accumulation, and then experience lower earnings growth. A key factor in this sorting result is the increased preference for earnings front loading induced by student debt. This effect is stronger for low ability individuals. Structural estimation highlights substantial non monetary returns to post bachelor education, that yields consumption-equivalent utility consisting of more than $30.000 per year. On the other hand, skills premium corresponds to less than 40% of the earnings differential between workers with a bachelor degree only and workers with additional education. Individuals with relatively higher ability are thus able to afford the cost of higher education given the mentioned composition of returns, while others postpone or choose the alternative career path. Two frictions are crucial in determining these results: binding credit constraints for leveraged households and limited ability to transfer human capital across careers. The second friction also helps explaining why indebted graduates do not simply enroll in graduate school after large part of their debt is repaid, since an implied cost of leaving their career is given by the destruction of part of their human capital accumulated on the job.

The model has also speaks to the effects of borrowing on home ownership. A first, intuitive channel, would point at higher borrowing causing reduced home ownership. On the other hand, career choice induced by the initial debt position is able to counterbalance this effect. Home ownership is relatively higher for young graduates that started their career with more student debt, a finding consistent with our empirical results. Unconstrained graduates who choose a career with a steeper earnings path (as is the case for those who enroll in graduate programs) are at the same time more likely to postpone their investment in housing. On the other hand, workers that choose to remain in a career that implies lower earnings growth consider housing a relatively more attractive investment. Student debt has the apparently counter intuitive effect of anticipating entry into home ownership. As workers age, those into careers characterized by a steeper income path eventually catch up on housing - both in the data and in the model, the two groups have the same rate of home ownership around age 37. These results point to an easy counterfactual exercise that helps highlighting the way in which, conversely, housing affects enrolment patterns. In a model without home ownership, distortions to human capital accumulation induced by student debt are smaller, enrolment in post bachelor programs is higher, and income inequality decreases. The main reason for this effect is that postponing household formation is costly: higher debt forces graduates to postpone additional education, or to invest less in human capital to accumulate higher savings. While doing so, workers realize that enrolling at a later age would mean a further postponement of household formation, as the downpayment constraint will bind for an even longer period of time, and choose give up on additional education or choose careers with a *flatter* income profile.

Finally, we use the model to evaluate the impact of a widespread adoption of an income based repayment plans (IRP) and compare it to a more radical forgiveness plan. We find that the introduction of the IRP provides the foundation for reducing the unintended consequences of student loan debt. By lowering an individual's monthly payments, IRP provides a consumption smoothing mechanism that reduces the need to choose a higher paying job. More surprisingly, the implementation of a forgiveness plan and the widespread adoption IRP yield similar outcomes.

The paper is organized as follows. **Section 2** summarizes the literature, **Section 3** describes the data and presents the empirical results, **Section 4** provides an overview of the model and the life cycle choices of individuals, **Section 5** calibrates and estimates the model to observed data patterns, **Section 6** presents the main results of the model, **Section 7** concludes with some policy discussion and future work.

2 Related Literature

This paper relates to the strand of research that aims at assessing the extent to which initial labor market conditions have strong effects on long term outcomes for earnings and wealth accumulation, as in **Kahn (2010)** and **Oreopoulos, Von Wachter and Heisz (2012)**. In particular, it places itself inside the literature that attempts to identify the impact of student loans on labor market outcomes after college. While research on student loans mostly relied on reduced form estimates, the broader literature on long term consequences of early career decisions is often based on structural models. In this work, we aim at bringing two branches of this literature together.

Isolating the effects of student debt on post graduate choices is made complex by student debt being typically negatively selected, as pointed out by **Looney and Yannelis (2015)**. The empirical evidence on how student debt affects earnings mostly points to a positive relationship, at least in the short run[2]. Based on a natural experiment in an elite university, **Rothstein and Rouse (2011)** show that student debt causes college graduates to choose jobs with an initial higher salary and reduces the probability that they choose "public" low paid jobs. **Luo and Mongey (2019)** find that a version of these results generalizes to the cross section of the U.S. colleges. In particular, they find that higher student debt causes college graduates to take jobs with higher wages, lower job satisfaction, and more on the job search.

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. **Chapman (2015)** finds that exogenously increasing the loan burden of a college graduate by $1,000 increases their income by $400-$800 one year after graduation. **Field (2009)** shows that law students who were offered loans were more likely to accept jobs in higher paying corporate law rather than public interest law.

Nonetheless, higher initial earnings may not necessarily lead to higher lifetime earnings if they are not followed by further human capital investment (**Becker (1962), Ben-Porath (1967), Hause (1972) and Mincer (1974)**). In this line of thought, **Fos, Liberman and Yannelis (2017)** investigate the effects of student debt on additional human capital investment measured as graduate school enrollment. They find that a $4,000 increase in student debt reduces the likelihood of enrollment in graduate school by 1.5 percentage points. In this paper, we contribute to this literature by considering general labor market outcomes for a nationally representative sample of college graduates. We also provide a unified framework for analyzing the relationship between student debt, earnings and human capital investment after college.

Another set of empirical articles have analyzed the role of student loans on first time home ownership. Controlling for multiple factors, **Houle and Berger (2015), Cooper and Wang (2014) and Gicheva and Thompson (2014)** show that student debt reduces the likelihood of homeownership for young households. This negative relationship likely reflects the underwriting process of a mortgage contract. First, student loans are due when borrowers have the least capacity to pay, leaving borrowers with a lower disposable income and less room for savings towards the down payment of a house. Second, and specially after the financial crisis, the inclusion of student loan payments in the debt to income ratio implies that some agents may delay home purchase until they can qualify for a (larger) mortgage.

Using administrative data and tuition induced variation in student debt, **Bleemer et al. (2017)** find that the recent increase in student debt could explain between 11 and 35 percent of the decline in young's homeownership over 2007-2015. Using a similar approach, **Mezza et al. (2016)** estimate that a $1,000 increase in student debt decreased first time homeownership by approximately 1.5 p.p. for public 4-year college graduates who left school between 1997 and 2005. We contribute to this literature by

[2]For empirical studies that conclude a negative or neutral effect of student debt on earnings see: **Weidner (2016)**, **Akers (2012)** , **Zhang (2013)**.

providing evidence of the effects of student debt on first time homeownership using new data on college graduates. In addition, we rationalize this relationship in a quantitative life cycle framework.

Our analysis also relates to the literature that study student loan program design within a quantitative framework. For example, **Ionescu (2009)** finds that repayment flexibility increases college enrollment significantly, whereas relaxation of eligibility requirements has little effect on enrollment or default rates. In a similar framework, **Ionescu and Simpson (2016)** find that tuition subsides increase aggregate welfare by increasing college investment and reducing default rates in the private market. **Johnson (2013)** also shows that tuition subsidies provide larger increases in college enrollments than increasing borrowing limits. Compared to this literature, our model provides a more detailed characterization of college graduates career choices and post schooling wealth accumulation.

In a related paper, **Di Maggio, Kalda and Yao (2019)** examine the effect of student debt forgiveness on individual credit and labor market outcomes. Using hand collected lawsuits filings matched with individual credit bureau information, they find that borrowers experiencing the debt relief shock reduce their overall indebtedness by 26%. They also find that borrowers' probability to change jobs increase after the discharge and this leads to an increase in earnings by more than $4000 over a three year period. We examine the effects of an hypothetical student debt forgiveness plan on both earnings and first time home ownership.

Finally, our paper relates to the literature that analyzes how initial conditions affect lifetime inequality. In particular, this literature focuses on the importance of initial conditions relative to shocks over the life cycle. **Huggett, Ventura and Yaron (2011)** study how heterogeneity in initial wealth and human capital affect lifetime inequality by modelling earnings growth through a Ben-Porath production function. They find that initial conditions, as measured at age 23, determine more than 60 percent of variation in lifetime utility, and that the majority of this variation is determined by initial human capital differences. In a similar framework, **Heathcote, Storesletten and Violante (2014)** use a model with heterogeneous preferences and productivity, and find instead that life cycle productivity shocks account for half of the cross sectional variance of wages.

The role of initial conditions in shaping long term human capital accumulation has been addressed in the search and matching literature as well. Using a model with directed search and heterogeneous asset holdings, **Griffy (2019)** finds that initial wealth plays a crucial role in determining life cycle inequality, and heterogeneity in skills has a relatively smaller impact. This difference is caused by the inclusion of frictional labor markets, which makes wealth have a first order effect on earnings. In a similar vein, **Eeckhout and Sepahsalari (2019)** show that there is positive sorting between workers with net asset holdings and more productive firms. In this article, we focus on college graduates and also find that initial wealth (student debt) plays a crucial role in life cycle decisions. Differently from this strand of literature, we model the labor market as career paths with different additional human capital requirements. We also include housing as a mechanism through which career choices could interact with financial constraints and affect lifetime wealth. Finally, our model is related to the one in **Athreya et al. (2019)**, as they build a life cycle model of education choice where agents are assumed to be heterogeneous in ability, liquid assets and human capital to understand the returns to college attendance for various segments of the population.

3 Data and Empirical Analysis

3.1 Description of Data

Our main source of data comes from the restricted use dataset from the National Center for Education Statistics (NCES) Baccalaureate and Beyond Survey (**B&B**). The survey follows several cohorts of bachelor's degree recipients over time and contains a mix of administrative and self reported data about their workforce participation, income, student debt, graduate school enrollment and homeownership (among many other variables).

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. B&B samples are representative of graduating seniors in all majors. The first cohort was drawn from the 1993 NPSAS and followed up in 1994, 1997, and 2003. The second cohort was drawn in 2000 and followed up in 2001. The third cohort was drawn from the 2008 NPSAS sample. Our analysis focuses on this last cohort, which was followed up in 2009 and 2012 and was interviewed again in 2018.

We restrict the sample to students who attended only one four year public college and responded to all interviews (2007-08, 2009, and 2012). Among these individuals, we focus on students that graduated at age 21-24. After imposing these restrictions, we also remove all colleges for which we do not have more than 10 students - this is necessary since we use an instrument that is based on college level variation and we need enough students per college for the sample to be representative.

Table 1 provides statistics for the whole sample and for the restricted sample. The table also provides CPS statistics for individuals with at least a BA degree and aged 22-25 in 2009 and 25-29 in 2012. Measures of earnings for Baccalaureate & Beyond for college graduates are similar to the ones in Census: the average earning for a college graduate in the restricted sample was \$27,082 right after college, while \$41,409 four years after graduation. Around 33 percent owned a house and approximately 26 percent had a Graduate Degree by 2012.

3.2 Empirical Estimation

We are interested in the effect of student loans on post baccalaureate enrollment (and other post college outcomes such as earnings and households formation). The relationship can be expressed in the following reduced form Equation:

$$y_i = \alpha g_i + \beta d_i + \gamma w_i + \epsilon_i \tag{1}$$

Table 1: Summary Statistics

	B&B 08/09/12		CPS
	Full Panel	Restricted Panel	Restricted
Outcomes			
2009			
Current primary job salary	29,007	27,082	29,153
2012			
Current primary job salary	41,869	41,409	43,886
Home ownership	37%	33%	38%
With a Graduate Degree	22%	26%	23%
Debt			
% Indebted	65%	60%	
Percentile 25 (d>0)	12,482	10,000	
Percentile 50 (d>0)	20,784	17,125	
Percentile 75 (d>0)	33,500	25,000	
College Obs.	1,442	186	
Individual Obs.	14,409	4,034	

Source: Baccalaureate and Beyond Longitudinal Study 2008/2012 and CPS 2009-2012.

where y_i is the individual's post college outcome, α is a vector that captures college fixed effects clustered in N groups, d_i is the log of the cumulative amount of loans (federal and private) borrowed for undergraduate degree at time of graduation, and w_i is a set of individual controls.

Isolating the causal effect of student debt is challenging, as borrowing is hardly an exogenous variable in students' decisions. In order to obtain an unbiased estimate of the causal effect of student debt, the regression should include all of the individual characteristics that affect the amount borrowed during college and the post baccalaureate decision.

To address this issue, we include a rich set of individual controls[3]. We include individual characteristics that are included in the FAFSA financial aid application form (financial need and dependency status), gender and ethnicity. We also include SAT and the major of study in order to account for individual's skills and ability.

Nonetheless, unobserved students' characteristics could still be relevant in determining access to different forms of aid; this makes d_i a potential endogenous variable, and thus, the OLS estimate of Equation (1) could be biased. The bias could go in either direction. On the one hand, if low ability students are less likely to receive grants, β will reflect the latent negative correlation between ability and borrowing. On the other hand, high ability students with higher earnings expectations could be more willing to borrow, resulting in debt being positively selected.

[3]See Appendix 1 for more details about how these variables are defined.

Figure 3: Grant to Aid (2007)

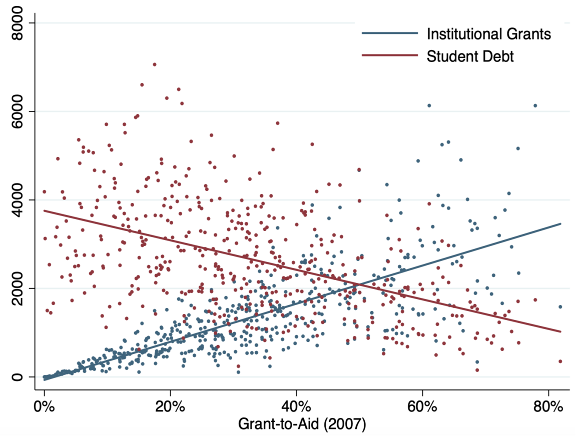


Table 2: First Stage Regression

	log(debt)
	(1)
Grant to Aid 2007	-0.039***
	[0.004]
Controls	Y
College FE	Y
Observations	4,034

Clustered standard errors in brackets

Figure 3 shows the average amount of institutional grants (in blue) and student debt (in red) by grant-to-aid for public colleges in the 2007/2008 academic year. Table 2 shows the regression output of the first-stage regression of cumulative debt at graduation on grant-to-aid in the 2007/2008 academic year. Source: IPEDS (2007) and Baccalaureate and Beyond Survey (2008). Standard errors are clustered by college groups, ordered according to the selectivity of admission.

3.3 Instrumental Variable: Institutional Grants

In this section, we show that supply side variations in the financial aid options faced by all students in a particular college offer a way to overcome the identification problem. In practice, students usually receive an aid package that is determined by college financial aid officers, but is not known in advance at the time of application. It includes grants, scholarships and loans. We focus on institutional grants, which are funded from private sources and net assets of the institution, include both need based and merit based grants, and they are available to incoming students as well as current students.

Since institutional grants do not require repayment, they are preferred to loans and are the first to be added into an aid package. Loans are therefore the marginal source of funds to most students, and change on an individual basis depending on how generous the institutional grant package is on any given year. Given that the total amount of financial aid (grants plus loans) available to students differs across colleges, we normalize institutional grants to the total amount of institutional grants and loans (grant to aid henceforth).

We define grant to aid as follows:

$$x_j = \frac{inst.grant_j}{(inst.grant_j + loan_j)}$$

Figure 3 shows how this ratio captures variations in both institutional grants and student debt: colleges with lower grant to aid offer aid packages with a higher component of student debt. Variations in the ratio coincide with a substitution between the two measures. The amount of college debt is thus modeled as an outcome of individual demand for debt and these supply side college variations in grants, represented by:

$$d_{i,j} = \rho g_i + \delta x_j + \phi w_i + u_i \tag{2}$$

We estimate the model by two stage regression. Therefore, it is important that there is significant variation of the instrument with student debt across institutions. **Table 2** shows that such condition is satisfied. The results imply that, on average, an increase in 1 percentage point in grant to aid induces a corresponding 3.9% decrease in student debt, all else equal.

In addition, grant to aid policies should be correlated with post baccalaureate enrollment (and other post college outcomes) only through student debt. The exclusion restriction may be violated if a college grant to aid policy is correlated with other individual characteristics, and those characteristics have a direct impact on students' post baccalaureate decisions. This may happen because students are not randomly assigned to a college and they choose college based on a bundle of college characteristics, that include financial aid availability[4].

To address this issue, we group public colleges into five different categories (N=5) based on the selectivity of admission (the classification is based on **Cunningham and Carroll (2005)**) and institutional Carnegie Classification[5]. **Table A1** shows that, once we control for college characteristics using the classifications described above, differences in grant to aid policies are not correlated with student to faculty ratio, graduation rate, retention rate, cost of attendance and other sources of grants (federal, state or local grants).

Although grant-to-aid is not correlated with college characteristics, students could still select into colleges based on institutional grants availability. However, the highest percentages of "very important" factors that influence college choice are quality/reputation, having a desired program of study, and job placement (**Ingels et al. (2011)**). This evidence is in line with grant to aid policies being uncorrelated with student characteristics such as income, ethnicity, SAT, and, percentage of full time students (**Table A2**).

Lastly, the amount of institutional grants available to students in a given college varies substantially over time (**Figure A1**). These changes make x_j even more uncertain for the student at the application stage and might come from surprise returns to university endowments - for instance, Harvard University endowment value declined 29.5% as investment returns reached -27.3% during the financial crisis. On the other hand, they might come from unexpected large donations - for example, take Michael Bloomberg's $1.8 billion donation in support of financial aid at John Hopkins University in 2018, that eliminated the need to borrow for prospective and current students.

[4] **Huntington-Klein (2016)** investigates the effects of the launch of College Scorecard online since September 2015 and find that it led to more searches for keywords associated with high earnings, high graduation rate, and low tuition.

[5] The classification we use groups college according to whether they are Doctorate granting Universities or Baccalaureate/Master's Colleges. For more on the Institutional Carnegie Classification, see **Shulman (2001)**

Table 3: Employment and post BA Completion

	Employed (2009) (1)	Employed (2012) (2)	post BA (2012) (3)
OLS	0.006***	0.002**	-0.004
	[0.001]	[0.001]	[0.003]
IV	0.044***	0.045***	-0.029***
	[0.011]	[0.004]	[0.010]
Controls	Y	Y	Y
College FE	Y	Y	Y
Observations	4,034	4,034	4,034

Standard errors, clustered by college groups, in brackets.

3.4 Empirical Results

3.4.1 Employment and Post Baccalaureate Enrollment

As of 2007-08, 30% of public college graduates aged 21-24 applied to graduate school and 60% reported they were planning to apply in the future[6]. Yet, only 26% of college graduates completed a post baccalaureate degree program four years later. This section analyzes the role of student debt on employment and graduate school enrollment choices.

Table 3 shows the average marginal effects from a Probit estimation of Equation (1) on employment status (employed but not enrolled in college) and post BA attainment 4 years after completing the Bachelor's degree. Column (1) implies that, on average, increasing a student's debt by 1% would lead to an increase in the probability of being employed (and not enrolled in college) by 4 percentage points. Column (2) runs the same equation 4 years after graduation and shows that the effect persists.

Column (3) shows the average marginal effects of debt on post BA attainment 4 years after graduation. Given that debt increases the probability of working (instead of enrolling), it's not surprising to see a significant negative effect of debt on graduate school attainment as of 2012. Ceteris paribus, a 1% increase in college debt reduces the probability of having a post baccalaureate degree four years after graduation by 2.9 percentage points.

3.4.2 Earnings and Households Formation

Results from the estimation of Equation (1) on earnings are given in **Table 4**. The first column shows the OLS and IV estimates for earnings one year after bachelor's degree completion. Column (1) implies that, on average, increasing a student's debt by 1% would lead to an increase in annual earnings of 0.28%. Column (2) runs the

[6] See **Wine et al. (2013)**

Table 4: Earnings and Households Formation

	Earnings		Household Formation		
	Wage 2009 (1)	Growth 2012 (2)	Homeownership (3)	Cohabitation (4)	House Value (5)
OLS	0.036**	-0.018	-0.000	0.010*	-0.016**
	[0.014]	[0.011]	[0.007]	[0.006]	[0.005]
IV	0.274***	-0.185***	0.018**	0.021***	-0.039**
	[0.045]	[0.062]	[0.008]	[0.007]	[0.020]
Controls	Y	Y	Y	Y	Y
College FE	Y	Y	Y	Y	Y
Observations	4,034	4,034	4,034	4,034	1,240

Standard errors, clustered by college groups, in brackets.

same equation on earnings growth 4 years after graduation and shows that the effect turns significantly negative.

The front loading effect of borrowing on earnings is consistent with the hypothesis that highly indebted graduates need to boost their initial earnings to ease the burden of repaying their loans. While part of this effect is certainly coming from indebted students being more likely to delay further education (and then reap the benefits some years after), we cannot rule out another channel represented by the choice of different career paths within the same educational requirements: for instance, a career with a steeper earnings process could be also characterized by the need to do some internship work after graduation before getting a full time position.

Columns (3) and (4) show the results of the estimation for home ownership and cohabitation with a spouse or partner. Measuring the impact of student loans on first entry into home ownership, being it inextricably linked with other life choices as career and household formation, is an important piece for validating our main hypothesis. Under the instrumental variable specification, we find that an increase in 1% in student debt increased the probability of being home owner four years after graduation by 1.8 p.p. Such a positive relationship is consistent with indebted students working more initially after graduating. Column (4) shows a similar positive effect of debt on cohabitation.

Notice, however, that differential earning expectations play a role in determining what type of home is bought. In fact, as more indebted workers enter earlier into homeownership, they also tend to buy less expensive homes: the elasticity of house value to student debt, shown in column (5) is large: considering the median home purchase is worth around $200.000, an elasticity of 3.9% implies a large effect on housing demand on the intensive margin.

3.4.3 Robustness

Additionally, following the main regression, we conduct multiple sensitivity analyses to provide further support for the IV estimation. First, we exploit variation in institutional grant-to-aid over-time and use as instruments both the grant-to-aid at enrollment (2003) and its change until graduation year:

$$x_j = \left(\frac{igrant_{j,07}}{(igrant_{j,07} + loan_{j,07})} - \frac{igrant_{j,03}}{(igrant_{j,03} + loan_{j,03})}\right)$$

As we can see in Column (2) of **Table A3**, the set of instruments are jointly relevant (Wald F statistic greater than 10). We then use this over-identified specification to test for endogeneity in the second stage regression. **Table A5** and **Table A6** shows the second-stage estimation results for this over identified specification and reports the Hansen J statistic (see **Sargan (1988)**) from the feasible efficient twostep over-identified estimation. The test is rejected for all specifications and the coefficient estimates from the over-identified specification are similar to the just identified estimation. This result points to the instrument being uncorrelated with other unmeasured college and individual characteristics.

Secondly, we estimate the effect of debt on a set of college performance characteristics. We deem relevant to see whether our instrumented measure of debt is correlated with college performance as it is itself an updated signal of individual's ability and surely an important factor for post baccalaureate education and employment status. We consider the following three as indicators of college performance : cumulative GPA at graduation, graduated with academic honors, and, placed on Dean's list. **Table A6** shows the estimates for both the OLS and IV estimation. As we can see, the OLS estimate hints at a possible negative selection on student debt. However, the IV estimates do not provide any significant difference in academic performance of indebted students. This result strengthens the argument that our IV estimate captures financial rather than academic effects of debt on post-college outcomes.

4 The Model

The model described in this section builds on important contributions to the human capital literature, as the career choice model of **Keane and Wolpin (1997)** and the **Ben-Porath (1967)** model presented in **Huggett, Ventura and Yaron (2011)**, extended to include student debt and housing.

A unit measure of finitely lived college graduates enter the labor market and are heterogeneous in student debt (d), human capital (h) and initial liquid wealth (k)[7]. Each household lives for T periods deterministically. During working age, workers can decide to enroll in grad 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

[7] The distribution of initial liquid wealth is calibrated to match after college parental transfers documented in **Haider and McGarry (2018)**

debt (if any).

4.1 Setting

Preferences. Each agent maximizes expected lifetime utility over non durable consumption (c) and housing services (s) (see textbfKaplan, Mitman and Violante (2019)):

$$u(c, s) = \frac{(c^{\zeta_1} s^{1-\zeta_1})^{1-\sigma}}{1-\sigma} \tag{1}$$

where c>0 and s=1+ζ_2, where ζ_2 is the housing service from owned housing.

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 careers and a linear production function, earnings are given by the human capital augmented number of hours worked multiplied by the equilibrium rental rate (R_t).

$$w_{j,t}(l_t, h_t) = R_t l_t \beta_j h_t \tag{2}$$

Workers are also exposed to unemployment risk: they can be separated from their job with probability ρ; while unemployed, they earn home production b, but cannot invest in human capital, so that $h_{t+1} = h_t$. When workers retire, they are assigned pension transfers that are proportional to their last earnings.

Careers and human capital. We restrict career choice to two different paths. In each career path, their compensation is equal to the marginal product of hours. Formally, normalizing rental rate $R_t = 1$, we get hourly wage $\tilde{w}_j = \beta_j h_j$, with $j = \{B, G\}$. The two paths differ in how workers' human capital accumulation translates into productive human capital. Human capital is less productive ($\beta_B < \beta_G$) for workers without graduate school education. Therefore, assuming workers make identical human capital investments, differences in earnings would grow as workers accumulate human capital.

After the career choice is made, individuals sequentially choose how much hours to work (l_t) and invest in further human capital ($1-l_t$). Human capital evolves according to the following Ben-Porath law of motion:

$$h_{t+1} = e^{z_{t+1}}(h_t + a((1-l_t)h_t)^{\alpha}), \quad z_{t+1} \sim N(\mu_z, \sigma_z^2) \tag{3}$$

which depends on individual's ability (a) and with risk coming from human capital idiosyncratic shocks. The Ben-Porath formulation implies that switching to the "steeper" career path that follows graduate school has three contrasting effects on human capital investment decisions. On the one hand, since earnings in the steeper career path loads more on human capital, investments are riskier. Formally, comparing variances of hourly wages: $\mathrm{Var}(\tilde{w}_G) = \beta_G^2 \mathrm{Var}(h) > \beta_B^2 \mathrm{Var}(h) = \mathrm{Var}(\tilde{w}_B)$.

Additionally, higher marginal product of human capital gives weaker incentives for graduate school educated worker to invest in human capital because of a simple wealth effect. On the other hand, $\beta_G > \beta_B$ generates 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. The third effect seems to be dominant in the data, suggesting that difference in career paths are amplified by endogenous human capital investment.

Graduate School. Individuals can enroll in graduate school while in working age: if they do, they attend for two years, and then start to work in their new career. While enrolled, human capital grows in every period at rate g_D, and workers consume using a combination of their liquid savings and a fixed benefit b_{grad}. They also get non monetary utility ξ, which summarizes the amenity value of being in school as opposed to working.

Also, while they can switch careers at any point, they would lose all the human capital associated with it 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 underinvestment in human capital.

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 that can depend on their current income (ϕ). If $k > 0$, savings yield a constant risk free rate r_+.

Student Loans. There are several options for repaying student loans, but the traditional and still most common 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. Student loan payments (P_τ) can be obtained as:

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

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. Graduate school debt is added to the students' balance, debt is consolidated and a new standard repayment plan is started, giving the worker 120 months to repay the full amount.

Housing. Workers can buy a house at any moment of their life - except when they are enrolled in graduate school - 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. Workers are also subject to housing preference shocks, which capture shifts in life events (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. If a worker chooses not to own their house, she has to rent (P_r). The rental price is tied to the price of the house, P_o, and is set to match a given price to rent ratio. Individuals can ask for a 30-year fixed mortgage (m) to pay the price of the house (P_o).

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. Apart from mortgage payments, home ownership involves benefits that individuals can't get from renting (such as tax deductions) and additional expenses (insurance and manteinance). We include these expenses (and benefits) as δ.

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_λ) until mortgage balances are zero, following:

$$P_\lambda = \frac{(1-\lambda)P_o}{\frac{(1+r_d)^{30}-1}{r_d(1+r_d)^{30}}} \tag{5}$$

4.2 Recursive formulation

We will illustrate the problem for agents of different stages of life, as the recursive formulation will differ according to it. The unit of time is two quarters. 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, 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^g indicates the value function of the worker with post-bachelor degree education.

Retired workers:

At retirement age $t = t_R$, workers are assigned pension transfers (p) that are proportional to their last earnings (w_{t_R-1}). Retired workers make consumption and saving decisions using their savings from working age (k_{t_R-1}). If they are home owners (o), they have to pay the residual parts of their mortgage (m) in equal payments (P_λ) until mortgage debt is fully paid off. Otherwise, if they are renters (r), they need to rent and pay P_0 every period. Retired workers cannot buy a house, as mortgage duration exceeds their life expectancy. We assume no bequests and terminal condition for liquid assets to be equal to zero.

Recursive Problem for renters, for $t = t_R, ..., T$, is :

$$V_{a,r,t}(k,w) = \max_{k'} u(c,s) + \beta V_{a,r,t+1}(k',w) \tag{6}$$

$$c + k' + P_r = (1+r)\cdot k + pw_{t_R-1}$$

$$m = 0, k_T = 0,\ k' \geq \phi(pw_{t_R-1}),\ c \geq 0,$$

The Problem for home owners for $t = t_R, ..., T$, with mortgage payment P_λ is:

$$
\begin{aligned}
V_{o,t}(a,k,w,m) = \max_{k'} u(c,s) + \beta V_{o,t+1}(a,k',w,m') \qquad (7)\\
c + k' + (P_\lambda + \delta) = (1+r)\cdot k + pw_{t_R-1}\\
m' = (1+r_d)m + P_\lambda\\
k_T = 0,\ k' \geq \phi(pw_{t_R-1}),\ c \geq 0
\end{aligned}
$$

In both cases, $r = r_+$ if $k \geq 0$, and $r = r_-$ otherwise. P_λ is the mortgage payment as defined in equation (5) and depends on the downpayment the homeowner chose at the time the mortgage was originated.

Workers (without student loans):

Agents enter working age ($t = 1, ..., t_{R-1}$), and face two discrete choices every period: which career to pursue, i.e. whether to enroll in graduate school ($j = \{B, G\}$), and whether to buy a house or not ($H = \{r, o\}$),. Workers' problem entails saving and choosing how much hours to work (l) and invest in further human capital (1-l) in every period. Human capital investment is risky and subject to an independent and identically distributed idiosyncratic shock every period (z). Earnings are given by the human capital augmented number of hours worked multiplied by the equilibrium rental rate as defined in (2).

Workers are also exposed to unemployment risk: while working (e=1), they can be exogenously separated from their job with probability ρ; while unemployed (e=0), they earn home production b, but cannot invest in human capital, so that $h' = h$. In order to ask for a mortgage and thus become a homeowner, workers have to satisfy the downpayment (λ) and at the same time satisfy the debt to income constraint (ψ). Once the mortgage is approved, the payments (P_λ) are fixed for the next 30 years as defined in (5).

The recursive problem for renters without graduate school education, while employed, is thus:

$$
\begin{aligned}
V_{a,r,t}(k,h,e) = \max_{k',l} \{u(c,s) + \beta \mathbb{E}[EV_{t+1}(a,k',h',e')]\} \qquad (8)\\
c + k' + P_r = (1+r)k + w_j(l,h)\\
h' = e^{z'}(h + a((1-l)h)^\alpha)\\
m' = (-\lambda P_o)[\mathbb{1}_{\frac{P_\lambda + P_r}{w_j} \leq \psi}][\mathbb{1}_{H=o}]\\
k' \geq \phi w_j,\ c \geq 0
\end{aligned}
$$

where:

$$
EV_t(a,k,h,e) = \max\left\{V_{r,t}(a,k,h,e), V^g_{r,t}(a,k,h,d_g,s), V_{o,t}(a,k,h,e,m), V^g_{o,t}(a,k,h,d_g,s,m)\right\}
$$

where V^g is the value function of a worker enrolled in grad school, and the states s, d^g indicate respectively periods of attendance and consolidated student loan balances. Unemployed workers' problem is analogous, with earnings replaced by b and no human capital investment decision. Unemployed workers can find a job in the same career with probability $1 - \rho$.

Home owners with housing payment P_λ face the following problem:

$$V_{o,t}(a, k, h, m, e) = \max_{k', l} u(c, s) + \beta \mathbb{E}\Big[EV_{o,t+1}(a, k', h', m', e')\Big] \tag{9}$$
$$c + k' + (P_\lambda + \delta) = (1 + r) \cdot k + w_j(l, h)$$
$$h' = e^{z'}(h + a((1 - l)h)^\alpha)$$
$$m' = (1 + r_d)m + P_\lambda$$
$$k' \geq \phi w_j, \;\; c \geq 0$$

where:

$$EV_{o,t}(a, k, h, m, e) = \max \big\{V_{o,t}(a, k, h, e, m), V^g_{o,t}(a, k, h, d_g, s, m)\big\}$$

If the worker is in the first period of home ownership, P_λ equals to the downpayment required to buy the house. After that period, housing payments are determined by the mortgage equation (5), as before.

At this point we want to characterize the recursive problem of the graduate school educated worker. For simplicity, we will characterize only the problem of the renter. Define $\bar{S}$ as the number of periods required to get the degree. For $s \leq \bar{S}$:

$$V^g_{r,t}(a, k, h, d_g, s) = \max_{k'} \big\{u(c, s) + \beta \mathbb{E}[V^g_{r,t+1}(a, k', h', d'_g, s')]\big\} \tag{10}$$
$$c + k' + P_r = (1 + r)k + b_{\text{grad}}$$
$$h' = h \cdot (1 + g_D)$$
$$k' \geq 0, \;\; c \geq 0$$

When $s > \bar{S}$, the recursive problem is analogous to the problem of a worker with student loans, conditional on career earnings' slope β_j, which is treated below.

Workers (with student loans):

Workers that enter the labor market with any positive amount of student debt ($d_0 > 0$) are by default enrolled in a 10-year fixed rate repayment plan, indicated by $\tau = 0$ [8]. Workers don't have the option of defaulting or deferring on student loan payments. An employed renter would solve:

[8] In this subsection both workers with undergraduate and graduate debt are treated together, assuming workers choose to consolidate their student loans at the day of graduation

$$V_{r,t}(k,h,j,d,e) = \max_{k',l} \{u(c,s) + \beta \mathbb{E}[EV_{t+1}(k',h',d',e')]\} \tag{11}$$

$$c + k' + (P_\tau + P_r) = (1+r) \cdot k + w_j(l,h)$$

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

$$d' = (1+r_d)d + P_\tau$$

$$m' = (-\lambda P_o)[\mathbb{1}_{\frac{P_\lambda + P_\tau}{w_j} \leq \psi}][\mathbb{1}_{H=o}]$$

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

where:

$$EV_t(a,k,h,d,e) = \max \Big[V_{r,t}(a,k,h,d,e), V^g_{r,t}(a,k,h,d_g,s),$$

$$V_{o,t}(a,k,h,e,d,m), V^g_{o,t}(a,k,h,d_g,s,m) \Big]$$

Home owners in working age with mortgage payment P_λ face the following problem:

$$V_{o,t}(a,k,h,m,d,e) = \max_{k',l} u(c,s) + \beta \mathbb{E}\Big[EV_{o,t+1}(a,k',h',d',m',e')\Big] \tag{12}$$

$$c + k' + (P_\tau + P_\lambda + \delta) = (1+r) \cdot k + w_j(l,h)$$

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

$$d' = (1+r_d)d + P_\tau \leq 0$$

$$m' = (1+r_d)m + P_\lambda \leq 0$$

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

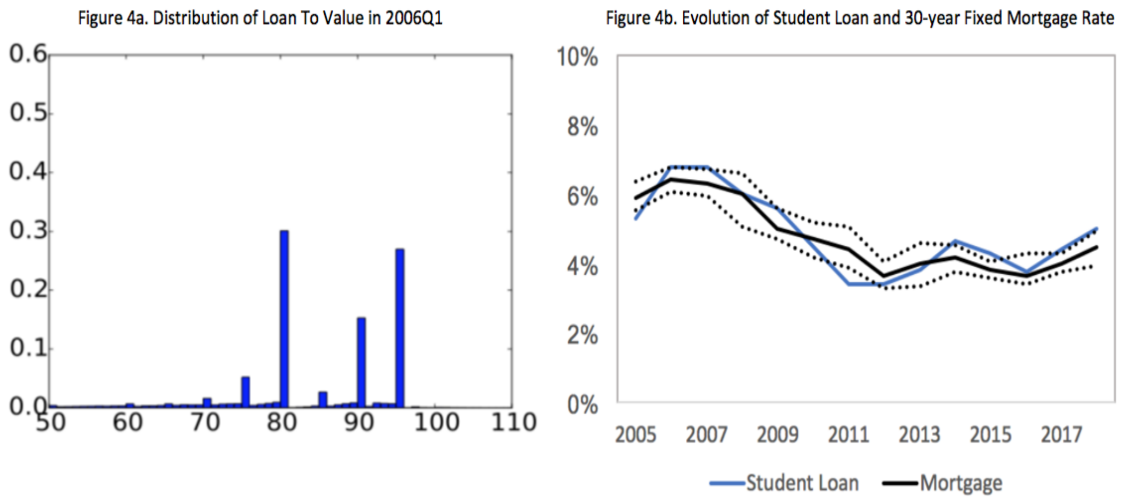
Where P_τ is the student debt payment as defined in equation (4), and where

$$EV_{o,t}(a,k,h,m,d,e) = \max \big\{ V_{o,t}(a,k,h,d,e,m), V^g_{o,t}(a,k,h,d_g,s,m) \big\}$$

5 Calibration and Estimation

In this section, we discuss how we determine the parameters required for the analysis. We set these parameters in two ways. First, we set some parameters from elsewhere in the literature or by using data estimation (**Table 5**). The remaining parameters are estimated using indirect inference through the model.

Figure 4: Loan to Value and Interest Rate on Student loan and Mortgage debt



Note: Figure 4a shows the distribution of the Loan To Value at origination in 2006Q1 (taken from **Greenwald (2018)**). Figure 4b shows the evolution of the federal student loan interest rate and the lowest, average and highest mortgage rate for a 30-year Fixed mortgage rate. Sources: Fannie Mae Single Family Dataset, Federal Student Aid, U.S. Department of Education, and, Freddie Mac's Primary Mortgage Market Survey (PMMS).

5.1 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 macroeconomics literature. The yearly discount factor is set to be 0.99. We set the constant relative risk aversion in the utility function to 2.

Career and Human Capital. Following **Huggett, Ventura and Yaron (2011)**, we set the mean shock of human capital to 0, with 0.075 variance and the production function parameter α to 0.66. We assume that, when unemployed, worker gains access to unemployment benefits that sum up to b calibrated to the Federal poverty threshold for an individual living alone in 2008 ($991 USD a month).

Labor Income. We set the rental rate to a yearly rate of 5% of the house price, and pension to be 45 percent of the last earned income. Finally, exogenous separation risk is set to 6 percent per year for bachelor-educated workers, and 4.5 percent for workers with a post-Bachelor degree, matching the average number of employment to unemployment transition of the two groups (see **Menzio, Telyukova and Visschers (2016)**).

Financial Markets and student debt. The annual interest rate for student loans and a 30-year fixed rate mortgage is calibrated to the 2004-2008 average rate of 6 percent (see **Figure 3b**). The risk free interest rate for savings is set at 0 following

Table 5: Calibrated Parameters

	Parameter	Value	Description
Preferences			
	β	0.99	Discount Rate
	σ	2	Risk Aversion
Careers, Human Capital			
	a	0.33	Average Learning Ability
	α	0.66	Ben-Porath Production Function
	μ_z	0.0	Mean Shock to Human Capital
	σ_z	0.075	Riskiness of Human Capital Investment
Labor Income			
	p	0.45	Pension Rate
	ρ	$\{0.045, 0.06\}$	Separation Probability
	b	\$991	Home Production (monthly)
Financial Markets, Student Debt			
	ϕ	$-$\$ 5,000	Credit Card Borrowing Limit
	r^+, r^-	$\{0.01, 0.05\}$	Interest on liquid assets
	r_d	0.035	Interest on student loans and mortgages
	τ	10	Years for Fixed Repayment Plan
Housing			
	P_o	\$ 200,000	House price
	λ	0.10	Downpayment (fraction of house price)
	ψ	0.43	Debt to Income Ratio

null real returns after 2008 and credit card borrowing rate is fixed at an annual 10 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 price of the house at the median home price in the U.S. (\$200,000). The rental price per year is set at 5% of the house value to match the price to rent ratio (20). To calibrate the additional costs of homeownership, we compare 2015 ACS data for the median gross rent (rent and utilities) and median homeownership cost (mortgage payments, real estate taxes, insurance and utilities) in each state. We find that the median cost to own a home is 50% more than the median cost to rent each month.

The parameters that determine the LTV and DTI are chosen to match institutional features of the US mortgage market. For the LTV parameter, fix a downpayment constraint of $0.2 \cdot P_o$. This value is intended to reflect the distribution of the LTV in Freddie Mac data, which has two masses point around 80% and 90% (see **Figure 3a**), where the first mass point is typically populated by younger buyers and thus seems more appropriate for pinning down the problem of first home ownership. 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 (Consumer Financial Protection Bureau 2013). Thus, we set the DTI parameter to 43%.

5.2 Distribution of Initial Characteristics

In order to simulate the model, we have to make parameter choices regarding ability, starting values of liquid assets, human capital and student debt. We assume students leave college with zero liquid assets, but receive an exogenous transfer ε_k from their parents, where $\log \varepsilon_k \sim \mathcal{N}(\mu_k, \sigma_k)$. Parameters of the log normal are calibrated to match parental transfers, as documented in **Haider and McGarry (2018)**, that report an average transfer of $15,275 with the average being $27,247 conditional on considering only the 56% of graduates that receive a positive amount from their parents.

The distribution of other initial characteristics (ability, human capital, and student debt) is jointly log normally distributed. We determine these parameters in multiple steps. We calibrate the initial mean and standard deviations of human capital to match the mean and standard deviation of earnings after graduation from CPS data - respectively at $32.590 and $22.152. We match an average debt balance of $16.619, as reported by B&B in 2008.[9] We assume no correlation between initial human capital and student debt, and we take the joint distribution of human capital and ability from **Athreya et al. (2019)**, who estimate a life cycle model of education choice on CPS data as well and report a correlation of 0.67.

Finally, we need to determine the mean level of ability, μ_a and its correlation with initial cumulated student debt, $\rho_{a,d}$. We set the first parameter in order to match an average growth rate of earnings of 1.9%. The second 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) with least squares. We estimate the second parameter, jointly with other structural parameters, to match the key properties of the earnings and homeownership profiles on CPS and B&B data.

5.3 Estimation

Parameters $\Theta = \{\xi, g_s, \beta_G, \zeta_1, \zeta_2, \rho_{a,d}\}$ are jointly estimated by Simulated Method of Moments (see **Gourieroux, Monfort and Renault (1993)** , **Smith Jr (1993)** and **Gallant and Tauchen (1996)**). Let 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 estimate 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:

$$g_n(\Theta) = \frac{1}{n}\left[\sum_{i=1}^{n} h(x_i) - \frac{1}{S}h(y_{i,s}(\Theta))\right] \tag{13}$$

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 more than 10000 times. In the case of a model with a large state space like ours, this could be computationally

[9] The figure is composed by a percentage of 66% of borrowers, with cumulative average balances of $22.560 and a standard deviation of $11.070

expensive.[10]. To overcome the curse of dimensionality, we discretize the parameter space using sparse grids (see **Bungartz and Griebel (2004)**) A similar approach in structural modelling as been using in the context of maximum likelihood estimation, see for instance **Heiss and Winschel (2008)**.

By using functions with support restricted to a neighborhood of each point to build $h(y_{i,s}(\Theta))$, our approach is suitable for approximating the parameter-moment mapping even in cases of sharp behavior, like large fluctuations of the gradient (see **Stoyanov (2013)**. Having $h(y_{i,s}(\Theta))$ at hand, we can construct an objective function that looks like:

$$\hat{\Theta} = \arg\min_{\Theta} g_n'(\Theta)\hat{W}_n g_n(\Theta) \tag{14}$$

where $\hat{W}_n$ is a positive definite matrix that converges in probability to a deterministic positive definite matrix W. We report results using an identity matrix for W. To construct the optimal weight matrix, we use the influence function technique from **Erickson and Whited (2002)** (see also **Bazdresch, Kahn and Whited (2017)** for an application closer to our case). Details of the implementation are in Appendix. Finding a solution to (14) faces the issue of the possible presence of many local minima: to make sure our solution is robust, we restart our optimization routine using multiple sets of starting values. Each routine solves its problem using a Nelder-Mead algorithm. Having an estimate of $h(y_{i,s}(\Theta))$ also allows us to obtain standard errors of parameter estimates, as they can be calculated knowing that

$$\mathrm{aVar}\left(\hat{\Theta}\right) = \left(1 + \frac{1}{S}\right)\left[\frac{\partial g_n(\Theta)}{\partial \Theta} W \frac{\partial g_n(\Theta)}{\partial \Theta'}\right]^{-1} \tag{15}$$

We want to match the empirical income profiles, the enrolment and the home ownership rates of individuals in working age. To do so, we take households with at least a BA degree, older than 23 years old from 2000-2018 Census data. We then separate the sample between those workers that obtained more than a bachelor degree at some point and those with only a bachelor degree. We use earnings in 2012 dollars, conditional on workers having a full time job, to calculate the income profiles. The six moments used in our estimation of the six parameters are computed as follows: we use the total student loan debt to income ratio at age 27, as we argue it proxies well both enrollment in additional education and the fact that it comes mostly from low indebted students. We then extract a constant and a linear trend from both the life cycle profiles of earnings and home ownership calculated from individuals aged 24-66 in Current Population Survey during years 2000-2018. In the first case, we use as a moment the ratio between constant and slope of earning profiles for workers with graduate degree and workers with only a bachelor degree. In the second case, we just aim at matching the overall life cycle profile of home ownership.

Table A10 displays parameter estimates. [11] Standard errors, in the second column,

[10] Using a cluster with 144 CPUs, we manage to obtain a full solution of the model and simulate it in about 14 minutes.

[11] The amenity value of grad school is expressed in dollar terms, but does not correspond to ξ. To

Table 6: Estimated Parameters

Parameter	Description	Value	Standard Dev.
ξ	Amenity Value of Grad School	\$55.171	\$16.795
g_s	Grad School HC growth	8.36%	0.15%
β_G/β_B	Skills Premium	14.25%	3.9%
ζ_1	Elasticity to Housing Service	0.539	0.0069
ζ_2	Housing Service	\$20.484	\$695
$\rho_{a,d}$	Correlation (ability, debt)	−12.4%	1.28%

Table 7: Target Moments

Moments	Mean	
	Data	Model
A. Sample Means		
Debt to Income at age 28[a]	0.59	0.59
Graduate to Bachelor Homeownership at age 38[c]	1.0	0.77
B. Regression Coefficients		
Home ownership, constant[b]	0.474	0.524
Home ownership, slope[b]	0.019	0.018
Graduate to Bachelor earnings ratio, constant[b]	1.10	1.04
Graduate to Bachelor earnings ratio, slope[b]	1.71	1.75

Sources:
a = B & B 2008 - 2012;
b = Current Population Survey, years 2000-2018, individuals with at least a bachelor degree, age 23-66, working full time
c = Current Population Survey, years 2000-2018, ratio between individuals with a bachelor degree and grad school education

tells us that estimates of parameters are precise - the only minor concern being represented by the objective function being less sensitive to changes in ξ. The model replicates well overall earnings dynamics, as in **Figure 5**. A better fit could be obtained by allowing a constant depreciation rate of human capital, which would induce a stronger concavity in the life cycle profile of earnings. However, the model matches pretty well average yearly income growth (1.9% in the data and 1.9% in our model), and earnings growth naturally slows because of income effects in the Ben-Porath problem. An extension of the model could perform the joint estimation of the Ben-Porath production function parameter and a linear depreciation rate of human capital.

While the model does not target anything but debt balances after graduation, it captures the front-loading incentives, as shown in **Table 8**: in the model, indebted

obtain it, we assume individuals in grad school are renters and have zero net liquid assets. Then the value is obtained by solving for the amount of consumption increase that would yield equivalent flow utility to grad school attendance.

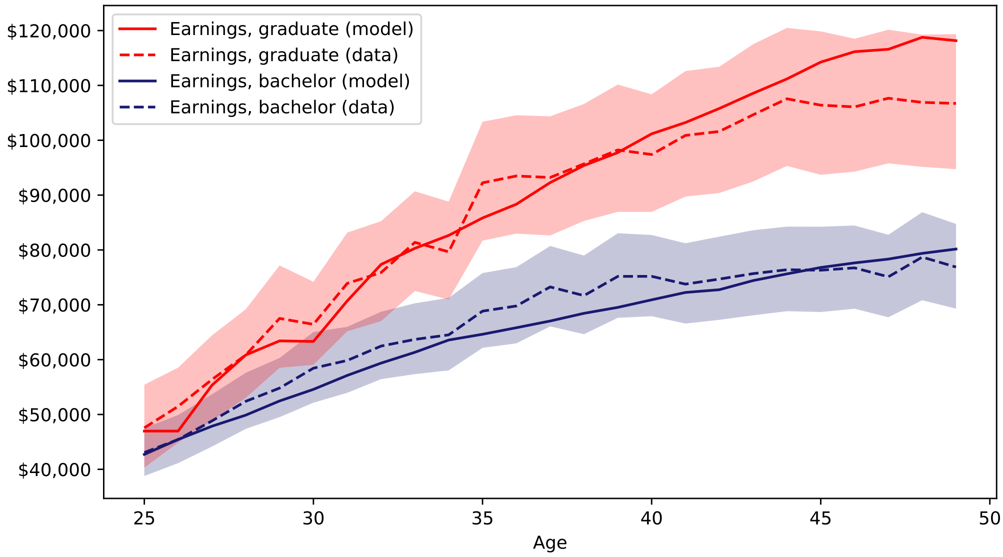
Table 8: Untargeted Moments

Moments	Mean	
	Data	Model
$\partial y_{t+1}/\partial d_t$	0.274	0.13
$\partial \Delta y_{t,t+4}/\partial d_t{}^a$	-0.185	-0.216

$\Delta y_{t,t+4}$ is the 4-year growth in earnings after graduation

graduates have 0.13% higher earnings for each 1% of additional student borrowing, but 0.26% lower earnings growth in the following four years.

Figure 5: Life Cycle Profiles for Income, Model and Data



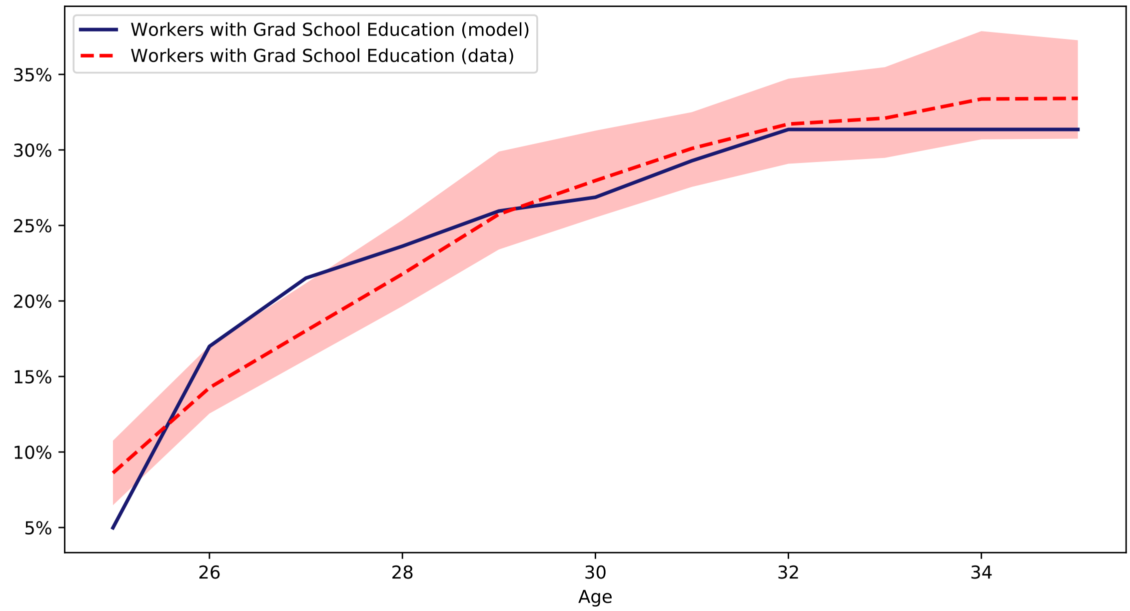
Data: Current Population Survey, years 2000-2018, population aged 24-66. Graduate School educated workers are all workers with an academic title higher than a 4-year college degree.

The patterns in enrollment, shown in **Figure 6**, replicates gradual entry into post graduate studies, and the level slightly more than a third of college educated workers pursuing further education. Because of the extreme assumption that human capital accumulated while working in one career is destroyed when switching[12], workers in the model tend to enroll slightly earlier than in the data. The slope in the life cycle pattern of home ownership in our model, as in **Figure 7**, is higher than in the data: especially in early years, home ownership is substantially lower, and then it catches up later in the working life. This can be explained with the choice of abstracting from bequest

[12]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.

shocks in the model, as they would allow households to anticipate home ownership by relaxing their budget constraint. Decomposing the rate of home ownership by educational level, as done later in the text, we can see that the delay in purchases is almost entirely attributable to workers that pursue graduate studies.

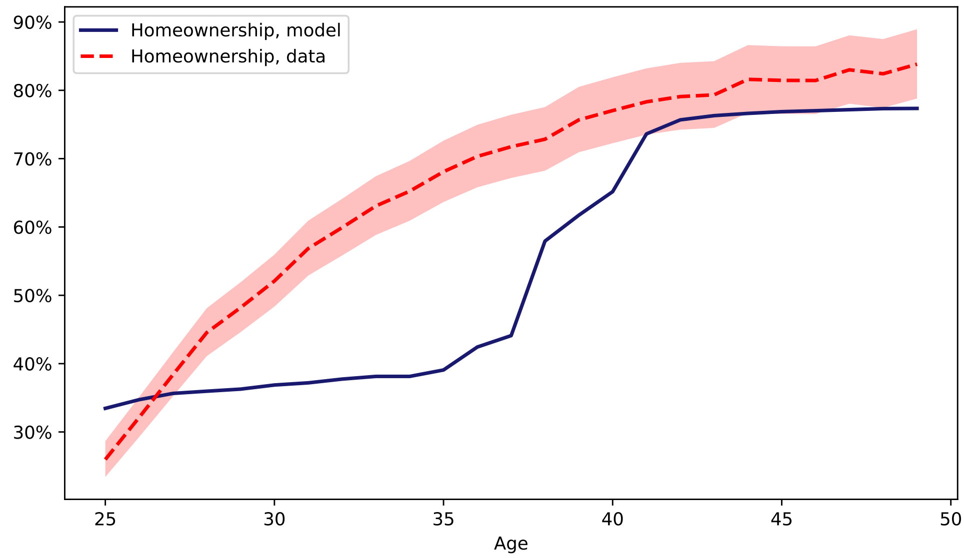
Figure 6: Life Cycle Profile of Enrollment in Graduate School



Data: Current Population Survey, years 2000-2018, population aged 23-66. Graduate School educated workers are all workers with an academic title higher than a 4-year college degree.

Another factor that limits earlier home purchases is our assumption of having just one size (and thus one price) available to workers. As results in the empirical section suggest, individuals who enter into homeownership earlier because college debt also purchase less expensive real estate. Extending the choice set by allowing individuals to differentiate their purchases with respect to price is the next step for improving the fit of our model to the data.

Figure 7: Life Cycle Profile of Entry into Home Ownership



Data: Current Population Survey, years 2000-2018, population aged 23-50.

5.4 Identification

The model generates a large number of moments that can be used for estimation. Since interactions between each choice 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, $\partial h(y_{i,s}(\Theta))/\partial\Theta$, has full rank. 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 - see **Bazdresch, Kahn and Whited (2017)**.

We use the ratio of home ownership at age 37 by education groups, when the ratio is 1, as a target moment. The flow value of housing, ζ_1 is identified by shifts in this ratio. The reason for this is that housing demand of workers with a post-bachelor degree is more sensitive to changes in the flow value: as it grows, not only less graduates enroll in post-bachelor programs, but workers with additional education try to enter into home ownership earlier, thus matching the home ownership of workers that only have a bachelor. A related parameter is the amenity value of graduate school: this, interestingly, is the value that mostly relates to the degree of sorting into additional education by ability, which in turn determines the ratio of the constants in income profiles. Hence, we can identify ξ by looking at shifts in the relative level of incomes between post-bachelor and bachelor-only educated workers. We want to know about the two earnings parameters; g_d ultimately determines the value of attending a post-bachelor degree. In the model, it also affects sorting, enrollment, and overall home ownership. However, only the relationship with the constant term in the home ownership life cycle profile is monotonous; as g_d grows, first increasing debt to income ratios. Then it also starts to allow more indebted workers to postpone enrollment, hence the ratio decreases without affecting the ratio of the earnings profiles. The most straightforward identifying relationship comes from simply increasing returns to graduate studies, thus allows more workers to enter into home ownership at some point in time. More intuitively, the skill premium β_g identifies the ratio of debt to income. The reason is that the skill premium, besides affecting earnings, is the main reason for increasing or decreasing early enrollment (remember the debt to income ratio is taken at age 25) in the model. Finally, we find that the correlation between debt and ability, $\rho_{a,d}$ is clearly identified by the ratio in the slopes of life cycle profiles of earnings. This is also intuitive: as the relationship between debt balances and ability becomes stronger (i.e. *more negative*), sorting into post bachelor degrees will unambiguously increase, other things not varying much. Hence, our model implies that growth in earnings differentials are mostly coming from increased borrowing of graduates with lower learning ability.

6 Results

In this section, we show the mechanisms behind the interaction between student debt, career choices and housing in our economy. We first analyze the performance of the baseline model in matching the empirical results presented in **Section 3**. We then provide some quantitative results that illustrate the contribution of each friction on the effects of debt on career choices and home ownership. Finally, we use the model to infer the effects of student debt on human capital and home ownership in the current environment.

6.1 The Increase in Student Debt from 2008 to 2016

We first use the model to perform a simple exercise: looking at changes in debt distribution. While this is hardly an exercise in model validation, as other important changes have occurred in the same decade, looking at a shift in debt distribution would give us important insights of the channels at work. In fact, looking at Table **9**, we can see that debt increased substantially during the Great Recession, then remained almost constant. Moreover, all the dynamics is concentrated on the intensive margin. As balanced increase by about 30% for borrowers, enrollment and earnings growth are affected the most in a scenario where nothing else changes from the baseline model. In particular, total enrollment decreases from 31.5% to 24% and earnings are 6% lower on average over the life cycle. Home ownership, by contrast, is barely affected, with 40% of workers being home owners at age 30, compared to 37% in the baseline scenario.

However, such large shifts in earnings and enrollment have not occurred, even if enrollment did slightly decrease after 2012 (see **Figure 2** The next sessions will highlight the different channels at play, and help understand what helped moderate the impact of increasing debt balances.

Table 9: Distribution of Cumulated Student Debt

	2008	2012	2016
Percent. Borrowers	66%	67%	63%
p10	\$5.000	\$7.000	\$6.000
p25	\$11.000	\$15.000	\$15.000
p50	\$20.000	\$27.000	\$27.000
p75	\$30.000	\$40.000	\$41.000
p90	\$45.000	\$56.000	\$59.000

Source: NPSAS 2008, 2012, 2016.
For each year, amount still owed on all undergraduate loans for students who graduated at that year and attended only one 4-year institution

6.2 The Role of Student Debt on Earnings and Wealth

There are two main tradeoffs involved in the initial career choice. First, workers that not pursue additional education start with higher disposable income but then have lower income growth compared to the more human capital intensive careers. Second, income paths of bachelor educated workers are less volatile as human capital accumulation is a risky investment. This is immediate if looking at models' predictions for income, as in **Table 10**. Workers whose undergraduate borrowing is above the median level start with higher earnings, because they are most likely to be working rather than being enrolled. After some years, the sorting effects of student loans start to affect earnings, and thus create a wide and persistent earnings gap.

Table 10: Earning Profiles by Debt Group

Undergraduate Student Loans	Amount Borrowed	
	< \$22.560	> \$22.560
Age 25	0.90	1.11
Age 28	1.036	0.94
Age 30	1.06	0.92

Simulated results from the model. Ratio of income to average income for the same age.

In absence of frictions to borrowing or to the ability to transfer of human capital across careers, student loans should have no effect on career choices and human capital investment. In our model, the effects of student loans on career choices and lifetime earnings are ultimately the result of three main frictions. First, young workers face credit constraints that limit their ability to self insure against negative realizations of their human capital investment, or to smooth consumption through prolonged periods of unemployment. Second, human capital is not fully transferable across careers: we assume that any experience accumulated in one career path is lost when the worker transfers to the other career.

The assumption of limited human capital transferability has important consequences on the choice of using the career with a lower loading on human capital as an initial way to earn higher wages. If the worker wants to move on to the graduate school later in life, the decision will bear costs that increase in his (or her) tenure on the job. Finally, student loans follow a predetermined fixed repayment schedule and alternative repayment schemes are limited.[13]

Table 11: Sorting into Post-Bachelor Degrees

Graduate School Enrollment	Student Debt		Total
	< $22.560	> $22.560	
Graduate School Enrollment at Age 25			
Low Ability	2.8%	2.33%	2.64%
High Ability	46.01%	32.25%	41.51%
Overall Graduate School Enrollment			
Low Ability	13.52%	11.20%	12.74%
High Ability	55.84%	43.80%	51.86%

Skill Groups: below and above median ability level

Table 13 shows how entry into graduate school is affected by borrowing. More indebted students are significantly less likely to enroll. This happens for two reasons: on the one hand, while attending school allows to postpone payments, 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. The value of switching, however, decreases with tenure for two reasons: one is the mentioned nontransferability of human capital across careers. The other is a simpler horizon effect: as the worker gets older, and approaches the age where it would be optimal to start a mortgage, attending graduate school would imply a postponement of entry into home ownership because of the binding downpayment constraint, reducing the value of additional education.[14] Interestingly, the largest impact of borrowing on enrolment is on individuals with higher ability. A dampened sorting into careers points on the second effect being dominant: in fact, while relatively low ability individuals enroll smoothly over post graduation years, high ability individuals who would postpone getting additional education and switching career find the option becoming increasingly costly as they get older.

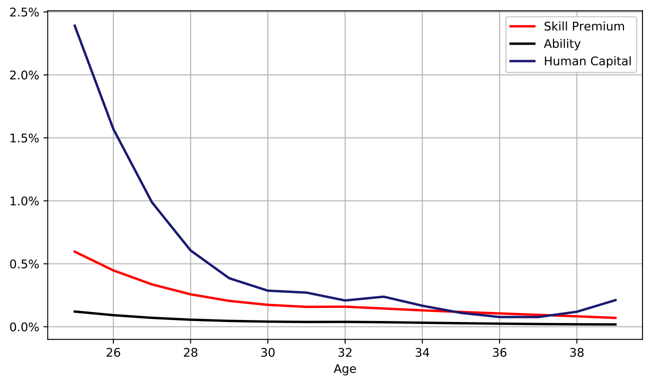
[13] Our empirical analysis is focused on graduates that entered the labor market in 2008: during those years, less than 7% of borrowers enrolled in plans that allowed payments to be linked to earnings. After a series of reforms, enrollment in income based plans has increased substantially in the following decade.

[14] We are not modelling household formation, and thus we are missing a potential counterbalancing effect, represented by adding a second income stream. However, as suggested by empirical evidence in the previous section, the impact of student debt on household formation goes in the same direction as the effects on home ownership. **Chang et al. (2019)** points out that the recent decline in home ownership can be attributed to delayed household formation, providing additional support to the view that housing purchase and marriage can be considered as a joint choice.

In order to understand the relative importance of different channels in affecting earnings over the life cycle, we decompose earnings growth differential between workers. To do so, we group workers based on different percentiles of student debt distribution. Notice one can obtain average earnings growth from **Equation** (3). Define s_G as the share of post bachelor educated workers in a given group, $\bar{a}$ as the average ability and $F(h)$ as the distribution of human capital in that group. Average earnings growth will be defined as:

$$\Delta(w) = \int \underbrace{(s_G\beta_G + (1 - s_G)\beta_B)}_{\text{skill prem.}} \underbrace{\bar{a}}_{\text{ability}} \underbrace{((1 - l)h)^{\alpha} dF(h)}_{\text{hum. capital}} \tag{16}$$

Figure 8: Decomposing Earnings Growth Differentials: Low versus High Debt



As argued above, highly indebted workers choose *flatter* earnings profiles. In **Figure 8** we decompose the earnings growth differentials between the lowest and the highest tercile of workers ordered by undergraduate borrowing. Interestingly, ability plays a minor role in determining earnings growth differentials. This comes from two aspects. First, model estimates deliver small correlation between initial ability and debt. More importantly, though, there is ex post sorting that depends on the fact that human capital accumulation is risky at the individual level. High ability - high debt individuals with good human capital realizations experience both high initial wage growth and lower rate of enrollment in post bachelor degrees, as the option value of switching career decreases substantially after their human capital (and thus earnings) reach a higher level, hence they stay in the labor force while workers with lower ability and the same realizations find enrollment more valuable and thus enroll (disappearing temporarily from the workforce). Differences given by skill premium are coming from different post bachelor degree attendance patterns, as highlighted in **Table 11**. As highly indebted students catch up on enrollment, the contribution of skill premium decreases, but remains positive and eventually becomes the main factor driving earnings growth differentials as human capital investment behavior reaches a *plateau* for most workers.

Finally, we find that endogeonous human capital accumulation contributes for the lion share of earnings growth differentials. Two effects go in the same direction in determining this result. As one can see from the policy function of workers for the

Ben-Porath human capital investment choice, highly indebted workers simply choose to invest less in order to have higher earnings in the current period. This is reinforced by career choices, as the same investment has higher returns for workers that enjoy a higher skill premium. This is consistent with earnings growth differentials being highest during the earlier years, as by **Figure 5**.

We now turn to housing. In our model, student loans affect home ownership through two main channels. On the one hand, highly indebted students are less likely likely to pursue extra education, which has lower returns to human capital, thus lower expected growth but also lower income risk. Thus, housing is a relatively more attractive investment at the start of the working career. On the other hand, student loan borrowers might face more difficulties in satisfying both the downpayment and the debt to income requirements for a mortgage. Since student loan payments reduce workers' disposable income, both investment in human capital and savings will be smaller. In addition, higher borrowing sorts workers into less human capital intensive careers, which negatively affects their lifetime earnings.

Table 12: Entry into Home Ownership

Age of First Purchase	Non Borrowers	Borrowers	
		$< \$22.560$	$> \$22.560$
Group			
All Workers	30	29	29
Only Bachelor[a]	25	26	28

a= includes those who do not enroll in grad school at any point in time

As shown in **Table 12**, all those effects play a decisive role in determining the age at which households purchase their first home. From the second row it is possible to see that, for those workers who don't choose to enroll in graduate studies, borrowing affects home ownership mostly through the wealth effect. Hence, borrowers enter into home ownership later, with the delay growing nonlinearly in debt balances. In the aggregate, however, the role of post-bachelor enrollment dominates. As we can observe from the first row, the larger share of enrollment of non borrowers pushes home ownership to later in life. As balances grow, the two effects compensate each other - from **Table 11** we know that less than 27% of highly indebted workers undertake graduate studies, against an enrollment rate of 33% in the overall population.

There is a role of heterogeneity in ability, however, that dampens the effects of borrowing: once all workers share the same learning ability parameter a, the delaying effect of graduate school is stronger (see **Table A11** in Appendix). This happens because in the alternative model the population of workers that pursue additional education now has a *lower* average learning ability, and thus it takes more time for them on average to reap the benefits of additional education in terms of earnings. Also, notice this happens despite the model estimated with no ability heterogeneity features larger skill premium.

Non indebted workers initially invest in additional human capital and undertake riskier career paths. In going to graduate school, they face some periods of lower earnings, and subsequently some years of lower disposable income (because they borrow more to pay for graduate school tuition). There is also a consumption smoothing motive that explains later entry into homeownership. Workers with lower debt balances enter into housing market later because, as they sort into careers with higher income growth, they also find it optimal to delay home ownership until they can post the downpayment without impacting their disposable income in a substantial way. These two factors cause them to delay buying a house until they can afford it later in the life cycle. Before that, investment in human capital is more attractive . On the other hand, those who face a lower expected wage growth value housing as a more attractive investment, and then purchase as early as possible.

Looking at disposable income distributions in **Figure A.11** (in Appendix) helps understanding how the two effects play a role. Workers with post college education will have higher earnings, but facing the down payment will still force many of them to compress current consumption substantially. Postponing entry into home ownership is then consistent with willingness to smooth consumption over time, as their expected consumption growth is larger. On the other hand, workers with only a bachelor degree will have to compress their consumption anyway, through multiple periods of sustained savings or by accepting a period of lower consumption.

However, since their expected income growth is lower and more predictable, value of waiting is lower, and thus many opt into an early entry into home ownership. In the context of our two careers, the delay is particularly likely given that . This could lower the home ownership rate at the beginning, especially for the young who do not have much wealth. On the other hand, the increase in risk induces workers to increase precautionary savings, until the downpayment constraint is not binding, and inducing more transition from renting to home purchase.

6.3 The Importance of Housing

To understand how relevant the housing channel is in determining education and career choices, we compare model predictions in a counterfactual scenario when workers are not allowed to access home ownership and remain renters during their whole life.[15] This way we are reducing available choices to workers compared to the baseline model, but we allow them to fully re-optimize given the new constraints they face. In this exercise, absent housing, agents can make different decisions about the timing of their investment in education (as well as about how much time to spend on human capital accumulation) than in the baseline.

[15] An equivalent assumption is that we are imposing $\zeta_2 = 0$ while leaving all other parameters unchanged from the baseline estimation

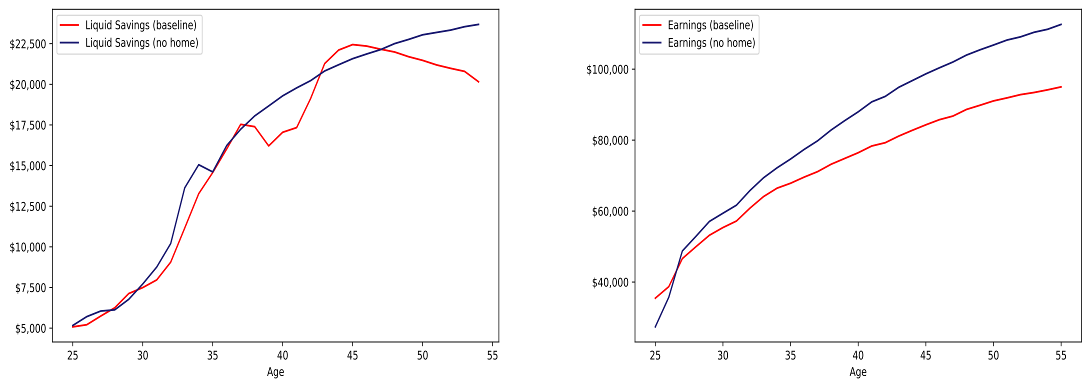
Table 13: Enrollment with and without Housing

Graduate School Enrollment	Student Debt		Total
	< \$22.560	> \$22.560	
Graduate School Enrollment at Age 25			
Baseline	24.4%	17.29%	22.03%
No Housing	52.83%	29.4%	45.02%
Overall Graduate School Enrollment			
Baseline	34.68%	27.50%	32.29%
No Housing	65.29%	45.84%	58.86%

Two clear trends emerge: first, enrollment increases for both groups, and it does even more for those who borrowed less. Second, while highly indebted students still choose to postpone enrollment in order to reduce their debt balances, they do eventually enroll in the following years, while the baseline model suggests strong horizon effects. Switching costs (i.e. limited transferability of human capital) and borrowing constraints still matter, and determine the difference in enrollment patterns between graduates with different debt balances. Notice, however, that even in this context enrollment should necessarily be identical along the debt distribution, to the extent that correlation with learning ability is different from zero - as turns out to be the case according to the estimates of our baseline model.

Figure 9: Baseline vs. no Homeownership

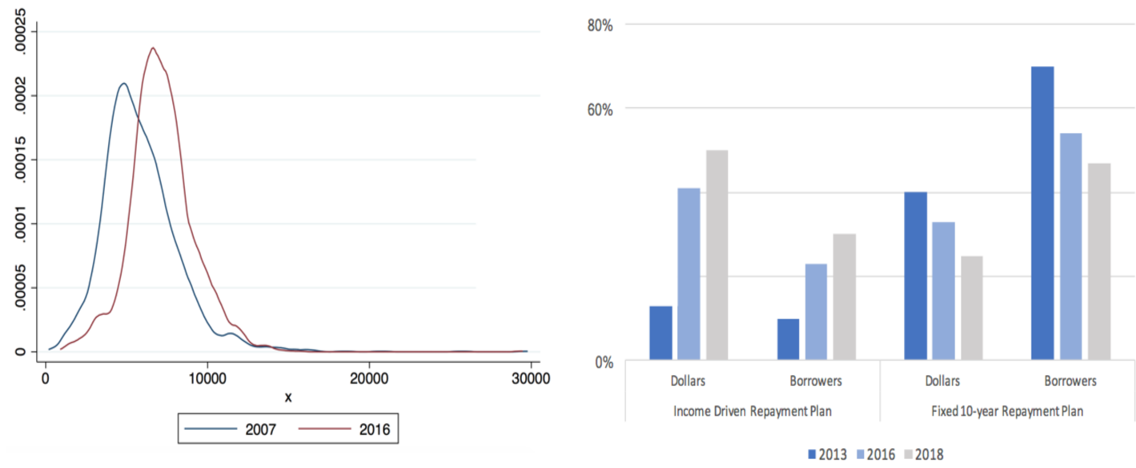
(a) Liquid Savings (b) Earnings



Increased enrollment in post-bachelor programs and the missing concern of savings in order to respect the downpayment constraint and then pay the mortgage have strong earnings effects, as shown in **Figure 9**. In this case, the change takes place mostly on the human capital investment side, as the pattern of savings is mostly unchanged - except for the later years, where a consumption smoothing motive drives workers in the counterfactual exercise into saving more.

6.4 A "Debt to Equity Swap": Income Based Repayment

Figure 10: Evolution of Student Debt and Repayment Plans



Note: Figure 10a shows the distribution of yearly student loans awarded to full time first time undergraduates for 2007 and 2016. Figure 10b shows the percentage of student loan borrowers enrolled in repayment plans as well as the percentage amount of student debt each repayment plan represents. Sources: The Integrated Postsecondary Education Data System (IPEDS) and the Federal Student Aid Data.

Income Based Repayment plans are 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)**). They became available in the US to federal loan borrowers and depend on the borrower's discretionary income. Unlike fixed payment plans, there is no set horizon of loan repayment; instead, the borrower pays a percentage γ of discretionary income each month until the loan is paid off or 20 to 25 years pass, in which case the remaining balance is forgiven (but included as taxable income). To be enrolled for these plans, borrowers have to report their income on an annual basis, and meet a series of eligibility criteria.

In this section, an income repayment plan in every period is introduced in the model as a baseline repayment scheme. The income repayment plan is defined to replicate the Pay As You Earn plan introduced in 2012: 10 percent of discretionary income for 20 years. At the end of the repayment period, remaining balances are forgiven and the forgiven amount is considered as additional income, to be taxed at a 25% rate. We rewrite the recursive problem in (11), as other problems are analogous:

$$V_{r,t}(k,h,j,d,e) = \max_{k',l}\{u(c,s) + \beta\mathbb{E}[EV_{t+1}(k',h',d',e')]\} \tag{17}$$

$$c + k' + P_r = (1+r)\cdot k + (1-\gamma)\cdot w_j(l,h)$$

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

$$d' = (1+r_d)d - \gamma \cdot w_j(l,h)$$

$$m' = (-\lambda P_o)[\mathbb{1}_{\frac{P_\lambda + P_\tau}{w_j}\le\psi}][\mathbb{1}_{H=o}]$$

$$k' \ge \phi w_j,\ \ c \ge 0$$

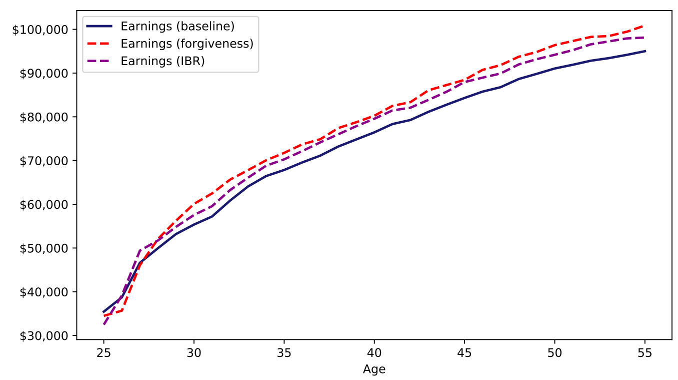
where:

$$EV_t(a,k,h,d,e) = \max\Bigg[V_{r,t}(a,k,h,d,e), V^g_{r,t}(a,k,h,d_g,s),$$
$$V_{o,t}(a,k,h,e,d,m), V^g_{o,t}(a,k,h,d_g,s,m)\Bigg]$$

It is not immediately clear how these 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 relative to income, increasing disposable income. On the other hand, it can extend the repayment period significantly relative to a 10-year plan, thereby potentially increasing the total interest paid by the student loan borrower over the life of the loan.

The latter effect is the main reason why enrollment under IBR rises, but due mostly to higher enrollment by high ability graduates (see **Figure 12**). However, facing increasing payments during age 25-35, and a small risk of having to pay a lump sum tax in the late 30s because of residual balance forgiveness, workers under IBR delay entry into home ownership even more. After age 45, income effects start to dominate and overall home ownership grows compared to baseline.

Figure 11: Baseline vs. Alternative Repayment Plans: Earnings



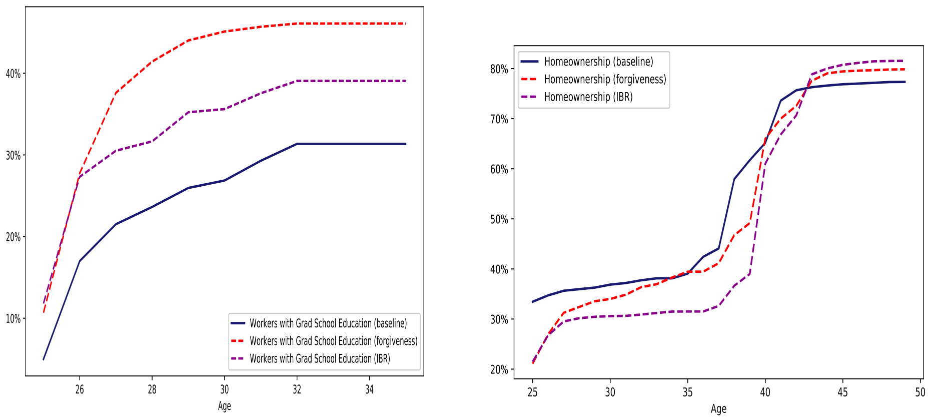
A final remark on IBR connects to the increase in balances discussed in **Section 6.2**: as shown in this section, linking repayment to income does help alleviating financial constraints. Even if the program did not achieve full participation of graduates, the growth in IBR enrollment shown in **Figure 10b** can be credited with moderating the impact of the dramatic growth in undergraduate debt balances occurred between 2008 and 2016.

6.5 Evaluating a Radical Policy: Debt Forgiveness for All

As student debt became a prominent issue in the public debate, various political actors have called for some sort of forgiveness plan. In this chapter we introduce debt forgiveness under a balanced budget constraint, assuming the government can forgive all debt and then finance this program by spreading lump sum taxation over the life cycle of workers. This policy experiment that should serve as a benchmark for evaluating a more realistic forgiveness plan, which would most likely include some form of conditionality, and not be universal. Moreover, any forgiveness plan is going to be financed at least in part with some form of income or consumption taxes.

Figure 12: Baseline vs. Alternative Repayment Plans: Enrollment and Housing

(a) Enrollment (b) Home ownership



According to our model, a forgiveness plan would have a large impact on post bachelor enrollment: it would both increase overall participation in graduate programs, and do it in particular doing early years. The second effect comes from the disappearance of the delaying motive that induces indebted graduates to postpone enrollment, while the first is a result of the relaxing of borrowing constraints on the same group. Given larger enrollment, it is not surprising that entry into home ownership is almost unchanged, as income effects move workers in the opposite direction. The overall impact on earnings and later age home ownership, however, are not substantially larger than under the Income Based Repayment alternative plan. This comes from the differential impact the two plans have on sorting into graduate school: IBR achieves higher enrollment by a sharp increase in the enrollment of high ability individuals. On the other hand, forgiveness has negative effects on sorting, as it mostly increases the participation of workers with lower learning ability. This has a large impact on endogenous human capital accumulation which, as shown in **Section 6.2**, is the main driver of earnings growth. Lower ability workers enroll at a higher rate (and borrow for graduate studies), but their net monetary gain is small, and their endogenous human capital investment in age 30-35 is reduced compared to the baseline scenario where they had repaid their residual debt by that age.

7 Conclusions

What are the implications of higher levels of student debt on life cycle decisions? We find that, on average, graduating with student debt causes earlier entry into home ownership, as well as higher earnings right after college, but lower income growth in the years after graduation. We then argue that this negative relationship is the result of student debt influencing career choices of college graduates. In particular, we find that individuals with higher levels of student debt are more likely to sort into careers that typically require less additional human capital after college, and specifically are less likely to enroll in post bachelor degree programs. We contribute to the existing literature by arguing that horizon effects determined by preferences for housing are an important channel for obtaining this result. While financial constraints are a necessary ingredient for initial financial conditions to affect life cycle outcomes, their interaction with a strong value attached to household formation is able to create a wide gap between outcomes of workers that start their careers with different debt balances.

Several policies have been advocated to help student loan borrowers. However, policy makers need guidance on the type of policies that are likely to be effective, from those that address liquidity constraints of borrowers to policies aimed to forgive a portion of student debt. We contribute to the policy debate by showing the merits of two alternative proposals. One, that is redistributive in nature, is to operate with a widespread forgiveness plan of all undergraduate debt, financed by lump sum taxes to be repayed over an extended period of time by the same cohort whose debt was forgiven. The other, that resembles closely the path chosen so far, aims at alleviating the burden of student debt by linking repayments to earnings. We show that an extension of existing policies is able to achieve results that are quantitatively very similar to more ambitious forgiveness programs - namely, that the income based repayment plans that already attract a significant number of graduates are already an effective policy to reduce career and human capital accumulation distortions induced by student borrowing.

In future work, we plan to move in two directions. The first is to endogenize the college borrowing decision, by modeling undergraduate attendance, and nest our life cycle structure into a general equilibrium, overlapping generations framework. Those extensions will allow us to investigate the pattern of increased college attendance of the last decades, identifying its causes among shifts in technology, preferences and policy. After doing that, we will aim at comparing more comprehensive policies regarding education financing, human capital, and life cycle decisions. Another important question to address requires extending the housing decision part of the model to allow for location choice, and to make location choice relevant for career considerations. The decline of interstate migration in the U.S. has long been associated with reduced labor market dynamism, although recent research pointed at it resulting from a reduction of the component of occupation specific human capital. In presence of location choices, housing becomes not only an investment, but can also a drag or an obstacle to geographical and labor mobility. Changes in labor markets can thus have interactions with financial constraints, and generate interesting macroeconomic implications.

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1 Appendix 1. Data

In this section we describe in more detail the data sources for the variables covered in Section 3.

A1.a B&B data

We use the restricted-use data and keep observations that have a positive value in the weight variable wte000, which represents the students who received a bachelor's degree in the 2007-08 academic year and responded to all interviews (2007-08, 2009, and 2012). The sample includes approximately 14,500 college graduates. We use and modify the following variables (available for public-use online in https://nces.ed.gov/datalab/powerstats):

<u>Debt Variables:</u>

Cumulative loan amount borrowed for undergraduate through 2007-08 (b1borat): Indicates the cumulative amount borrowed from all sources for the respondent's undergraduate education through June 30, 2008. Does not include Parent PLUS loans.

Cumulative federal loans borrowed for undergraduate through 2007-08 (fedcum1): Indicates cumulative amount borrowed in federal loans for the respondent's undergraduate education through June 30, 2008. Does not include Parent PLUS loans.

<u>Outcome Variables:</u>

2012 Current Primary Job Salary (b2cjsal): Indicates the respondent's annualized salary from their current or most recent primary job. Primary job is defined as the respondent's current or most recent job that lasted more than 3 months. We replace with a zero value the earnings of those who were not working at the time of the interview but reported the most recent earnings.

2009 Current Primary Job Salary (b1erninc): Indicates the respondent's income from their current job as of the B&B:09 interview. For respondents with multiple jobs, salary is only for the primary job, the job at which the respondent worked the most hours.

Employment and Enrollment Status in 2009 and 2012 (b1lfp09 and b2lfp12): Indicates the respondent's level of labor force participation and enrollment as of the BB:09 interview. Variable categories are: One full time job, enrolled; One full time job, not enrolled; One part time job, enrolled; One part time job, not enrolled; Multiple jobs, enrolled, Multiple jobs, not enrolled; Unemployed, enrolled; Unemployed, not enrolled; Out of the labor force, enrolled; Out of the labor force, not enrolled.

2012 Current Value of Primary Residence (b2fhomval): Indicates the approximate current value of the respondent's home(s), as reported by the respondent in the B&B:12 interview. We classify as home owners those observations with a value higher than zero.

Completed Master's Degree Program as of 2012 (b2macmp): Identifies whether the respondent had completed a master's

<u>College Fixed Effects:</u>

Selectivity of College (selectv2): Indicates the level of selectivity of the 2007-08 bachelor's degree granting institution. Only applies to public and private nonprofit 4-year institutions; other institutions were set to zero. Variable categories are: Not public or private nonprofit 4-year, Very selective, Moderately selective, Minimally selective, and Open admission. We classify them in two groups: low/medium selective (Moderately selective, Minimally selective, and Open admission) and very selective

Carnegie code (2000) for 2007-08 institution (CC2000): The 2000 Carnegie Classification includes all colleges and universities in the United States that are degree-granting and accredited by an agency recognized by the U.S. Secretary of Education. The 2000 edition classifies institutions based on their degree-granting activities from 1995-96 through 1997-98. Variable categories are: Doctoral/research universities-extensive; Doctoral/research universities-intensive; Master's colleges and universities I; Master's colleges and universities II; Baccalaureate colleges-liberal arts...and For-profit degree granting.

<u>Individual Controls:</u>

Student budget minus EFC in 2007-08 (sneed1): Indicates the respondent's total need for need-based financial aid in 2007-08.

Dependency status in 2007/2008 (depend): Indicates the respondent's dependency status during the 2007-08 academic year. Variable categories are: Dependent and Independent.

SAT I score (tesatder): Indicates the respondent's SAT I combined score, derived as either the sum of SAT I verbal and math scores or the ACT composite score converted to an estimated SAT I combined score using a concordance table from the following source: Dorans, N.J. (1999). Correspondences Between ACT and SAT I Scores (College Board Report No. 99-1).

Field of Study (majors4y): Indicates the respondent's major or field of study, using 10 categories, for the 2007-08 bachelor's degree. Variable categories are: Computer and information sciences; Engineering and engineering technology; Bio and phys science, sci tech, math, agriculture; General studies and other; Social Sciences, Humanities, Health-care, Business, Education and Other Applied. We classify them in three categories: STEM and health-care, Social Sciences and Business, Other.

Race/Ethnicity (race): Indicates the respondent's race/ethnicity with Hispanic or Latino origin as a separate category. Variable categories are: White, Black or African American, Hispanic or Latino, Asian, American Indian or Alaska Native, Native Hawaiian, other and More than one race. We classify them into four categories: White, Black or Latino, Asian, Other.

Gender (gender): Indicates the respondent's sex. Variable categories are: Male and Female.

A1.b IPEDS data

Using harmonized college identifiers, we merge the B&B individual level data with institution level from the Institutional Post-Secondary Database (**IPEDS**). We use the IPEDS data in order to get information about the cost of attendance as well as the amount of grants and loans at the institutional level. We use the following variables for 2004-2007 from the IPEDS data center:

<u>College Student Debt:</u>

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.

<u>Institutional Grants:</u>

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. Includes scholarships targeted to certain individuals (e.g., based on state of residence, major field of study, athletic team participation) for which the institution designates the recipient.

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).

<u>Grant-to-Aid:</u>

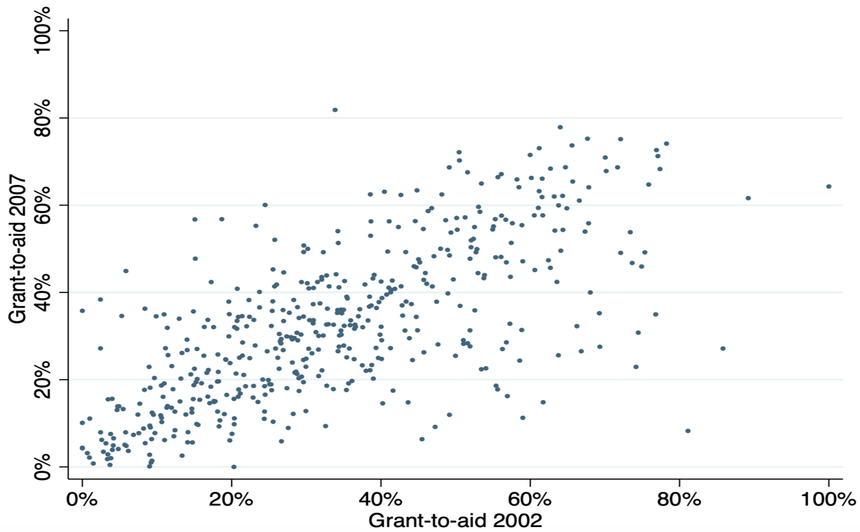
Some of the institutions have a missing value in grants or loans and at the same time the percentage of students who were awarded grants or loans is zero. We substitute these observations with a zero value in grants or loans. We then drop 6 colleges that still had some missing value in grants or loans in any of the six years (2002-2007).

Given that the average sum (and percent) of institutional grant and loan amounts are not available for 2002-2007, we construct the total institutional grant-to-aid ratio in the following way:

$$aid_{j,t} = ploan_{j,t} loan_{j,t} + pgrant_{j,t} grant_{j,t} = \left(\frac{TotalDebt_{j,t}}{Indebted_{j,t}}\right)\left(\frac{Indebted_{j,t}}{Students_{j,t}}\right) + \left(\frac{Grant_{j,t}}{Recipient_{j,t}}\right)\left(\frac{Recipient_{j,t}}{Students_{j,t}}\right)$$

$$x_{j,t} = \frac{\left(\frac{Grant_{j,t}}{Recipient_{j,t}}\right)\left(\frac{Recipient_{j,t}}{Students_{j,t}}\right)}{aid_{j,t}}$$

Figure A1: Evolution of Grant-to-Aid



Note: authors calculations. Source: IPEDS (2002-2007).

Table A1: Grant-to-Aid and College Characteristics

	Stud/Faculty (1)	Grad. Rate (2)	Ret. Rate (3)	log(Cost) (4)	log(Gov Grant) (5)
No College FE	-0.158	0.251***	0.118***	8.73*	-5.11
	[0.252]	[0.042]	[0.027]	[4.87]	[0.000]
College FE	-0.316	0.080	0.101	-5.102	-2.09
	[0.412]	[0.476]	[0.231]	[10.142]	[3.606]
Observations	476	476	476	476	476

Standard errors in brackets.

Table A2: Grant-to-Aid and Undergraduate Students Characteristics

	% Black (1)	%Age<25 (2)	%Full-time (3)	Avg. SAT (4)	% Income < 48,000 (5)
No College FE	-0.099***	0.030	-0.011	0.128***	0.136**
	[0.032]	[0.078]	[0.028]	[0.016]	[0.060]
College FE	-0.07	-0.194	-0.169*	0.102	0.033
	[0.045]	[0.113]	[0.071]	[0.057]	[0.158]
Observations	476	476	476	364	476

Standard errors in brackets.

Appendix 2. Empirical Results (Including Covariates)

Table A3: First Stage Regression

	log(debt)
Grant to Aid 2007	-0.039***
	[0.004]
Mod. Select. (BA/MA)	-0.886***
	[0.021]
Mod. Select. (Doctoral/Research)	-0.881***
	[0.028]
Very Select. (BA/MA)	-1.054***
	[0.027]
Very Select. (Doctoral/Research)	-0.939***
	[0.05]
log(Financial Need)	-0.339***
	[0.042]
log(SAT)	-1.201
	[0.605]
Dependent	-0.382
	[0.337]
Black or Latino	0.506**
	[0.167]
Asian	0.0752
	[0.283]
Other race	0.108
	[0.540]
Female	0.264
	[0.198]
Computer and Information sciences	-0.298
	[1.873]
Engineering	-0.862*
	[0.393]
Science and Math	-1.021***
	[0.181]
General Studies	0.151
	[0.800]
Humanities	-0.525*
	[0.242]
Health care	-0.268
	[0.363]
Business	0.0638
	[0.192]
Education	0.026
	[0.262]
Other Applied	0.303
	[0.294]
Constant	8.419***
	[0.305]
Observations	4,034

Standard errors, clustered by college groups, in brackets.

Table A4: Employment and post-BA Completion

	Employed (2009) (1)	Employed (2012) (2)	post-BA (2012) (3)
log(debt 2008)	0.124***	0.129***	-0.089***
	[0.038]	[0.010]	[0.031]
Mod. Select. (BA/MA)	0.0849	0.230***	-0.135***
	[0.068]	[0.014]	[0.044]
Mod. Select. (Doctoral/Research)	0.132***	0.222***	-0.077***
	[0.034]	[0.011]	[0.030]
Very Select. (BA/MA)	0.075	0.215***	-0.009
	[0.087]	[0.022]	[0.070]
Very Select. (Doctoral/Research)	0.168***	0.108***	-0.168***
	[0.036]	[0.003]	[0.020]
log(Financial Need)	-0.042***	-0.057***	0.022
	[0.017]	[0.008]	[0.021]
log(SAT)	0.038	0.229	0.522***
	[0.336]	[0.249]	[0.166]
Dependent	0.195***	0.113	-0.371***
	[0.055]	[0.098]	[0.022]
Black or Latino	-0.282***	-0.237***	0.171***
	[0.052]	[0.058]	[0.016]
Asian	-0.271***	-0.367***	0.022
	[0.107]	[0.042]	[0.09]
Other race	-0.168**	-0.280***	0.130
	[0.086]	[0.087]	[0.107]
Female	0.007	-0.010	0.034
	[0.0444]	[0.059]	[0.093]
Computer and Information sciences	0.935***	0.813**	-0.710***
	[0.078]	[0.401]	[0.119]
Engineering	0.489***	0.632***	-0.50***
	[0.117]	[0.072]	[0.143]
Science and Math	-0.043	0.061	-0.175
	[0.238]	[0.153]	[0.220]
General Studies	0.120	-0.03	-0.249
	[0.254]	[0.192]	[0.218]
Humanities	0.087	0.086	-0.252***
	[0.166]	[0.122]	[0.08]
Health care	0.209**	0.231	-0.259*
	[0.102]	[0.155]	[0.144]
Business	0.453***	0.377***	-0.436***
	[0.105]	[0.122]	[0.066]
Education	0.433***	-0.059	-0.039
	[0.037]	[0.141]	[0.084]
Other Applied	0.306***	0.314***	-0.466***
	[0.041]	[0.098]	[0.081]
Constant	-0.598**	-0.664***	0.267
	[0.299]	[0.100]	[0.258]
Observations	4,034	4,034	4,034

Standard errors, clustered by college groups, in brackets.

Table A5: Earnings and Households Formation

	Wage 2009 (1)	Growth 2012 (2)	Homeownership (3)	Cohabitation (4)
log(debt 2008)	0.276***	-0.185***	0.050**	0.053***
	[0.046]	[0.062]	[0.022]	[0.018]
Mod. Select. (BA/MA)	-0.597***	0.606***	-0.108***	-0.001
	[0.101]	[0.079]	[0.031]	[0.019]
Mod. Select. (Doct./Res.)	-0.234***	0.302***	-0.186***	0.022
	[0.045]	[0.077]	[0.031]	[0.024]
Very Select. (BA/MA)	-0.595***	0.506***	-0.310***	0.021
	[0.143]	[0.120]	[0.035]	[0.019]
Very Select. (Doct./Res.)	-0.186***	0.255***	0.042**	0.035
	[0.061]	[0.061]	[0.021]	[0.025]
log(Financial Need)	-0.118***	0.073***	-0.049***	-0.053***
	[0.034]	[0.026]	[0.010]	[0.012]
log(SAT)	0.912	1.28***	-0.447***	-0.083
	[0.626]	[0.206]	[0.109]	[0.129]
Dependent	0.602***	-0.669***	0.472***	0.496***
	[0.182]	[0.0922]	[0.0381]	[0.071]
Black or Latino	-0.363***	0.251	-0.248***	-0.477***
	[0.099]	[0.248]	[0.083]	[0.052]
Asian	-1.25***	0.573	-0.586***	-0.654***
	[0.420]	[0.410]	[0.090]	[0.055]
Other race	0.723***	-0.217	0.197***	0.167
	[0.132]	[0.204]	[0.0686]	[0.198]
Female	0.053	0.019	0.145***	0.285***
	[0.091]	[0.084]	[0.044]	[0.062]
Comp. sciences	1.870***	-0.301	0.546***	-0.125
	[0.223]	[0.306]	[0.121]	[0.242]
Engineering	1.955***	-0.401*	0.892***	0.344***
	[0.281]	[0.232]	[0.124]	[0.132]
Science and Math	-0.357	0.108	0.047	0.252***
	[0.518]	[0.421]	[0.109]	[0.055]
General Studies	-0.224	1.04***	0.132	-0.103
	[0.422]	[0.331]	[0.093]	[0.104]
	...	...	...	...

Table A5 (cont.): Earnings and Households Formation

	Wage 2009	Growth 2012	Homeownership	Cohabitation
	(1)	(2)	(3)	(4)
Humanities	-0.221	0.521	-0.100***	0.065
	[0.574]	[0.434]	[0.013]	[0.057]
Health care	0.753	0.078	0.695***	0.465***
	[0.664]	[0.620]	[0.110]	[0.166]
Business	0.869*	0.016	0.403***	0.119
	[0.464]	[0.470]	[0.150]	[0.184]
Education	1.081***	-0.711*	0.502***	0.328***
	[0.354]	[0.381]	[0.074]	[0.062]
Other Applied	0.400	0.011	-0.005	0.089
	[0.339]	[0.256]	[0.067]	[0.055]
Constant	6.955***	1.922***	-0.967***	-0.700***
	[0.582]	[0.353]	[0.125]	[0.088]
Observations	4,034	4,034	4,034	4,034

Standard errors, clustered by college groups, in brackets.

Appendix 3. Empirical Results (robustness)

A3.a Over-identified IV

Table A5: First Stage Regression

	log(debt)
Grant to Aid 2002	-0.040***
	[0.006]
Δ Grant to Aid 2007	-0.033***
	[0.003]
Wald F Statistic	39.241
Controls and College FE	Y
Observations	4,034

Standard errors, clustered by college groups, in brackets.

Table A6: Employment and post-BA Completion

	Employed (2009) (1)	Employed (2012) (2)	post-BA (2012) (3)
log(debt)	0.050***	0.045***	-0.029***
	[0.014]	[0.004]	[0.009]
Controls and College FE	Y	Y	Y
J statistic (p-val)	0.1892	0.557	0.218
Observations	4,034	4,034	4,034

Standard errors, clustered by college groups, in brackets.

Table A7: Earnings and Households Formation

	Earnings		Households Formation	
	Wage 2009 (1)	Growth 2012 (2)	Homeownership (3)	Cohabitation (4)
log(debt)	0.292***	-0.203***	0.021***	0.021***
	[0.042]	[0.072]	[0.005]	[0.006]
Controls and College FE	Y	Y	Y	Y
J statistic (p-val)	0.177	0.285	0.118	0.970
Observations	4,034	4,034	4,034	4,034

Standard errors, clustered by college groups, in brackets.

A3.b College Performance

Table A8: College Performance

	GPA (1)	Academic Honors (2)	Dean's List (3)
OLS	-0.795***	-0.011***	-0.004
	[0.176]	[0.001]	[0.003]
IV	0.875	0.018	0.018
	[1.45]	[0.021]	[0.021]
Controls and College FE	Y	Y	Y
Observations	4,034	4,034	4,034

Standard errors, clustered by college groups, in brackets.

A3.c Bivariate IV Probit

Table A9: Bivariate IV Probit: Predicted Margins

	Indebted 2008			
Grant-to-Aid 2007	-0.010***			
	[0.002]			
	Employed 2009 (1)	Post-BA 2012 (2)	Homeownership 2012 (3)	Cohabitation 2012 (4)
Indebted 2008	0.241***	-0.232***	0.105*	0.123**
	[0.074]	[0.101]	[0.057]	[0.049]
Controls and College FE	Y	Y	Y	Y
Observations	4,034	4,034	4,034	4,034

Standard errors, clustered by college groups, in brackets.

Appendix 4. Solution Method

A4.a 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 (11). 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:

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

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 et al. (1973)**.

Taking again the value function in (11). Abstracting from career and repayment choice, and focusing only on the home-ownership decision, the expected value of the future value function becomes:

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

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

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

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

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

A4.b Borrowing constraints

Solving (2) 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.

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

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:

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

and

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

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:

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

Appendix 5. Optimal Weight Matrix for GMM

We follow **Erickson and Whited (2002)** in computing the optimal weight matrix $\hat{\Omega}^{-1}$ from the following formula for clustered covariance:

$$\hat{\Omega} = \frac{1}{nT}\sum_{i=1}^{n}\left(\sum_{t=1}^{T}\psi_{h(x_{i,t}))}\right)\left(\sum_{t=1}^{T}\psi_{h(x_{i,t}))}\right)' \tag{9}$$

in which $\psi_{h(x_{i,t}}$ is the vector of influence functions for the empirical moments $h(x_{i,t})$. Deriving the influence functions for choice of moments is relatively straightforward. Take any subset of $h(x_{i,t})$ and denote it as θ. For those moments that are obtained from simple averages, i.e. $\hat{\theta} = \mathbb{E}(x_i)$, the influence function can be computed simply as:

$$\psi_{\hat{\theta}}(x) = x - \mathbb{E}(X) \tag{10}$$

In the case of linear regression coefficients, we need to get influence function for the slope and the constant. The slope is $\hat{\theta}(\beta) = \frac{\mathrm{Cov}(X,Y)}{\mathrm{Var}(X)}$. Then:

$$\begin{aligned}\psi_{\hat{\theta}(\beta)}(x,y) &= \frac{(x-\mathbb{E}(X))\,(y-\mathbb{E}(Y)) - \mathrm{Cov}(X,Y)}{\mathrm{Var}(X)} - \frac{\left((x-\mathbb{E}(X))^2 - \mathrm{Var}(X)\right)\mathrm{Cov}(X,Y)}{(\mathrm{Var}(X))^2} = \\ &= \frac{(x-\mathbb{E}(X))\,(y-\mathbb{E}(Y)) - \beta\,(x-\mathbb{E}(X))}{\mathrm{Var}(X)} = \frac{(x-\mathbb{E}(X))}{\mathrm{Var}(X)}\left[(y-\mathbb{E}(Y)) - \beta\,(x-\mathbb{E}(X))\right]\end{aligned} \tag{11}$$

The constant is instead $\hat{\theta}(\alpha) = \mathbb{E}(y) - \frac{\mathrm{Cov}(X,Y)}{\mathrm{Var}(X)}\mathbb{E}(x) = \mathbb{E}(y) - \frac{\mathbb{E}(XY)\mathbb{E}(X) - (\mathbb{E}(X))^2\mathbb{E}(Y)}{\mathrm{Var}(X)}$. Then:

$$\begin{aligned}\psi_{\hat{\theta}(\alpha)}(x,y) = &-\frac{(xy-\mathbb{E}(XY))\,\mathbb{E}(X) + (x-\mathbb{E}(X))\,\mathbb{E}(XY) - (y-\mathbb{E}(Y))\,(\mathbb{E}(X))^2 - 2\,(x-\mathbb{E}(X))\,\mathbb{E}(X)\mathbb{E}(Y)}{\mathrm{Var}(X)} + \\ &+ y - \mathbb{E}(Y) + \frac{\left((x-\mathbb{E}(X))^2 - \mathrm{Var}(X)\right)\left(\mathbb{E}(XY)\mathbb{E}(X) - (\mathbb{E}(X))^2\,\mathbb{E}(Y)\right)}{(\mathrm{Var}(X))^2} = y - \mathbb{E}(Y) - \\ &- \frac{(xy - y\mathbb{E}(X))\,\mathbb{E}(X) + (x-\mathbb{E}(X))\,(\mathrm{Cov}(XY) - \mathbb{E}(X)\mathbb{E}(Y))}{\mathrm{Var}(X)} - \frac{\left((x-\mathbb{E}(X))^2 - \mathrm{Var}(X)\right)}{(\mathrm{Var}(X))^2}\end{aligned} \tag{12}$$

Finally, we use the ratio of regression coefficients. Take the ratio of slopes $\hat{\theta}(\beta_g/\beta_b)$. Then by the chain rule:

$$\psi_{\hat{\theta}(\beta_g/\beta_b)}(x_g,y_g,x_b,y_b) = \frac{\psi_{\hat{\theta}(\alpha)}(x_g,y_g)\beta_b - \psi_{\hat{\theta}(\alpha)}(x_b,y_b)\beta_g}{\beta_b^2} \tag{13}$$

And similarly, one can obtain the influence function for the ratio of constants.

Appendix 6. Model without heterogeneity in ability

We estimate the same model as in **Section 5**, assuming no heterogeneity in ability.

Table A10: Estimated Parameters

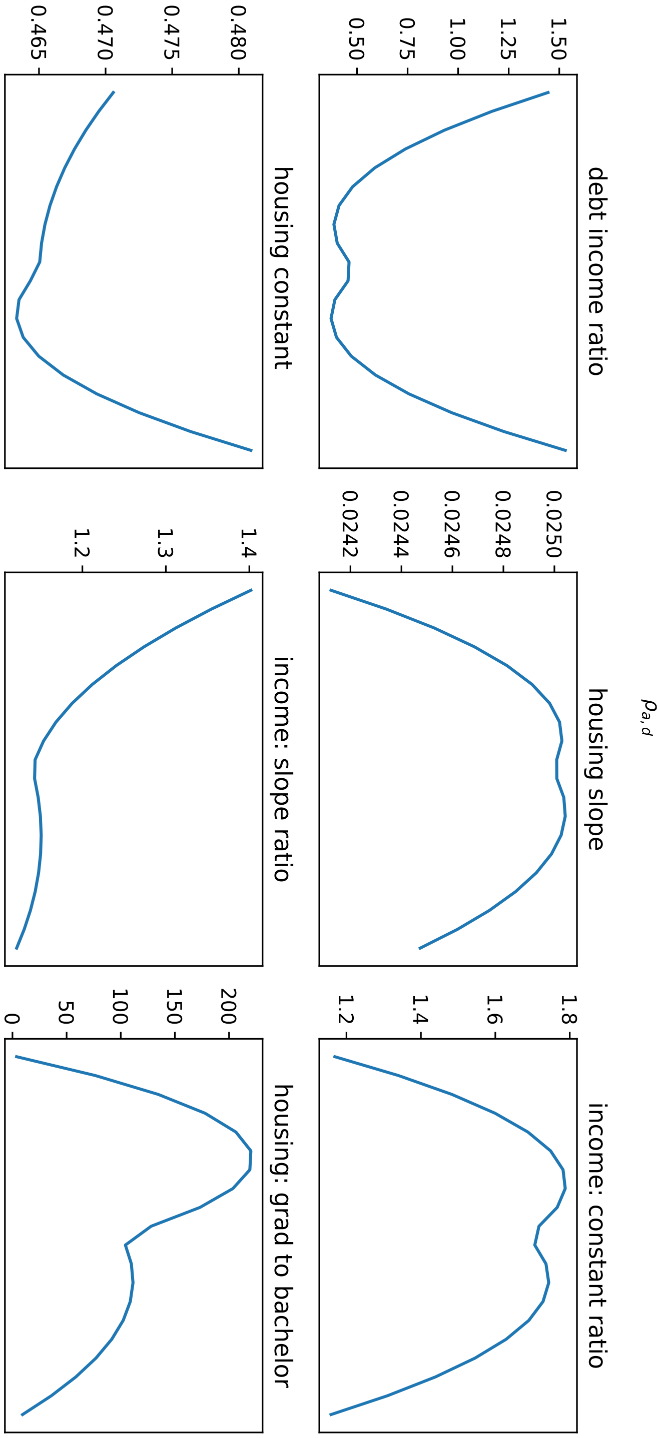
Parameter	Description	Value	Standard Dev.
ξ	Amenity Value of Grad School	\$74.080	\$18.080
g_s	Grad School HC growth	8.99%	0.23%
β_G	Skills Premium	12.7%	2.4%
ζ_1	Elasticity to Housing Service	0.605	0.005
ζ_2	Housing Service	\$22.760	\$920

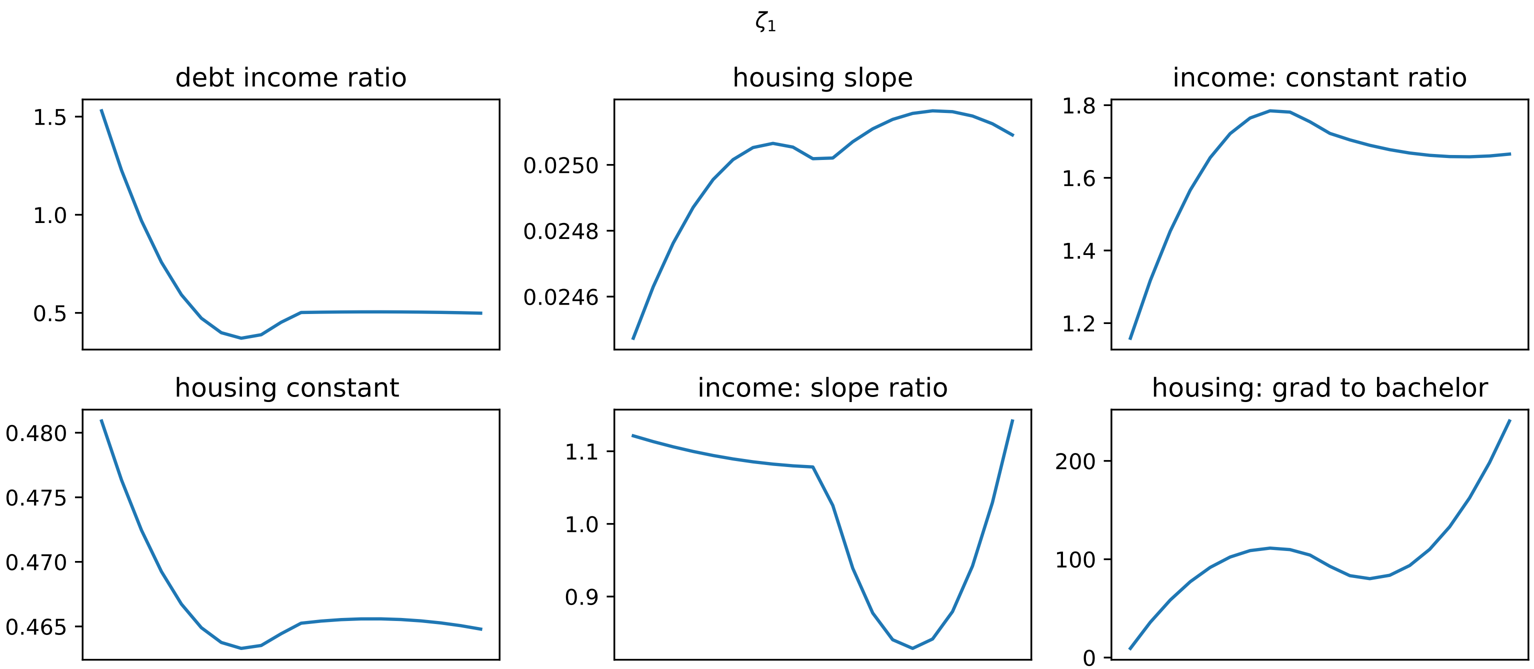
Table A11: Entry into Home Ownership

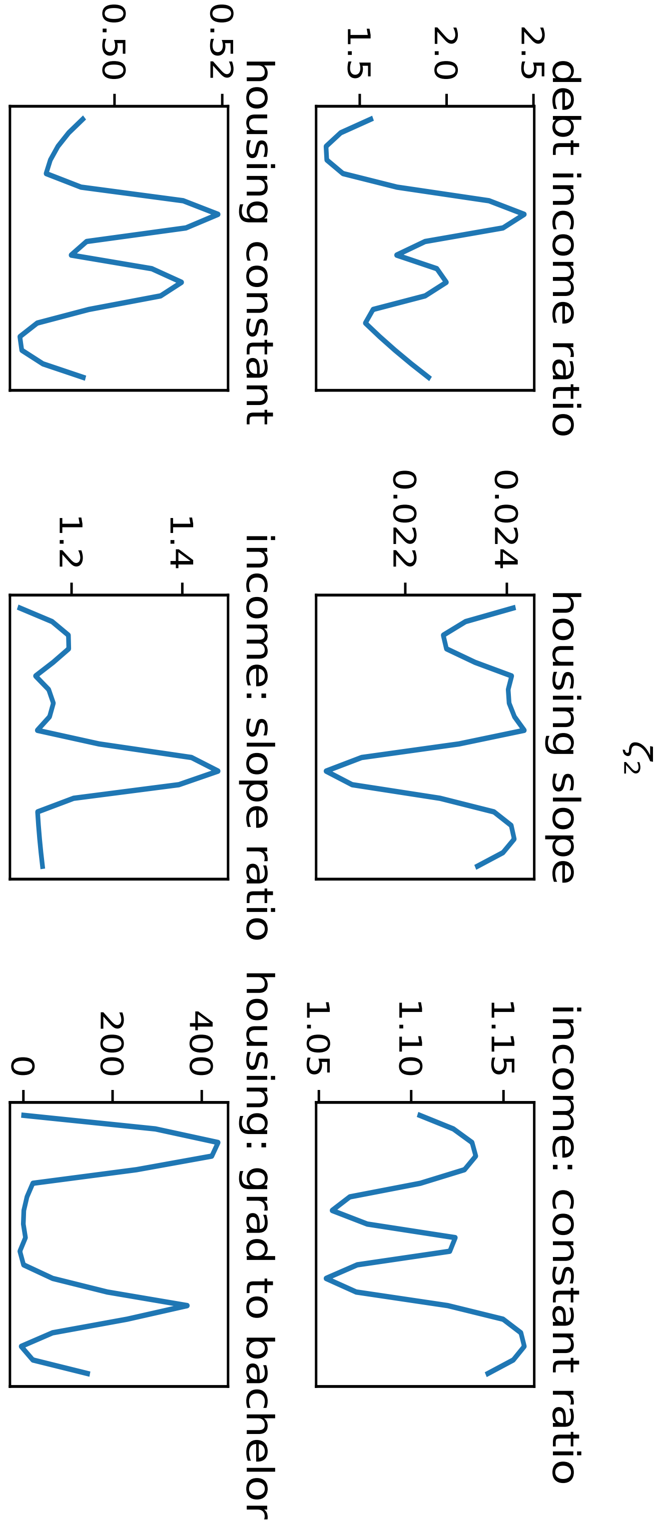
Age of First Purchase	Non Borrowers	Borrowers	
		< \$22.560	> \$22.560
Group			
All Workers	34	26	29
Only Bachelor[a]	24	25	28

a= includes those who do not enroll in grad school at any point in time

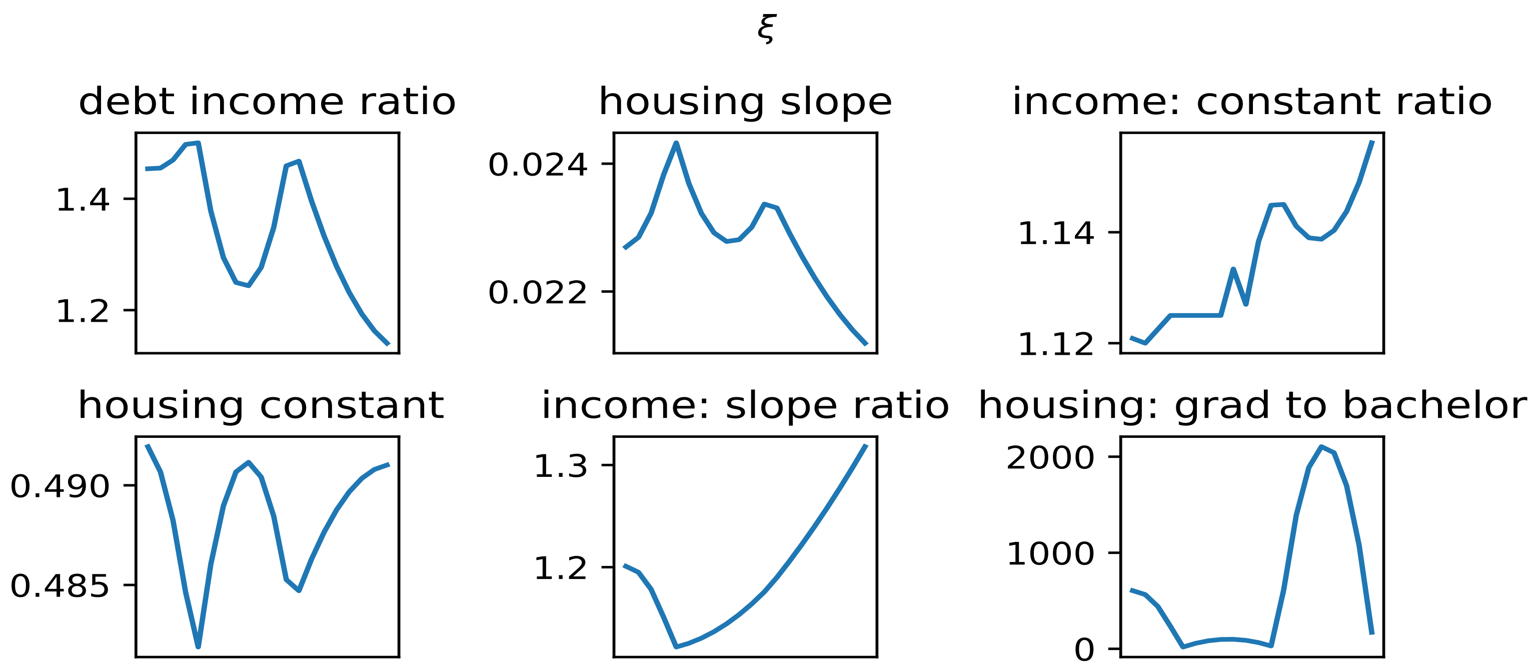
Appendix 7. Identification



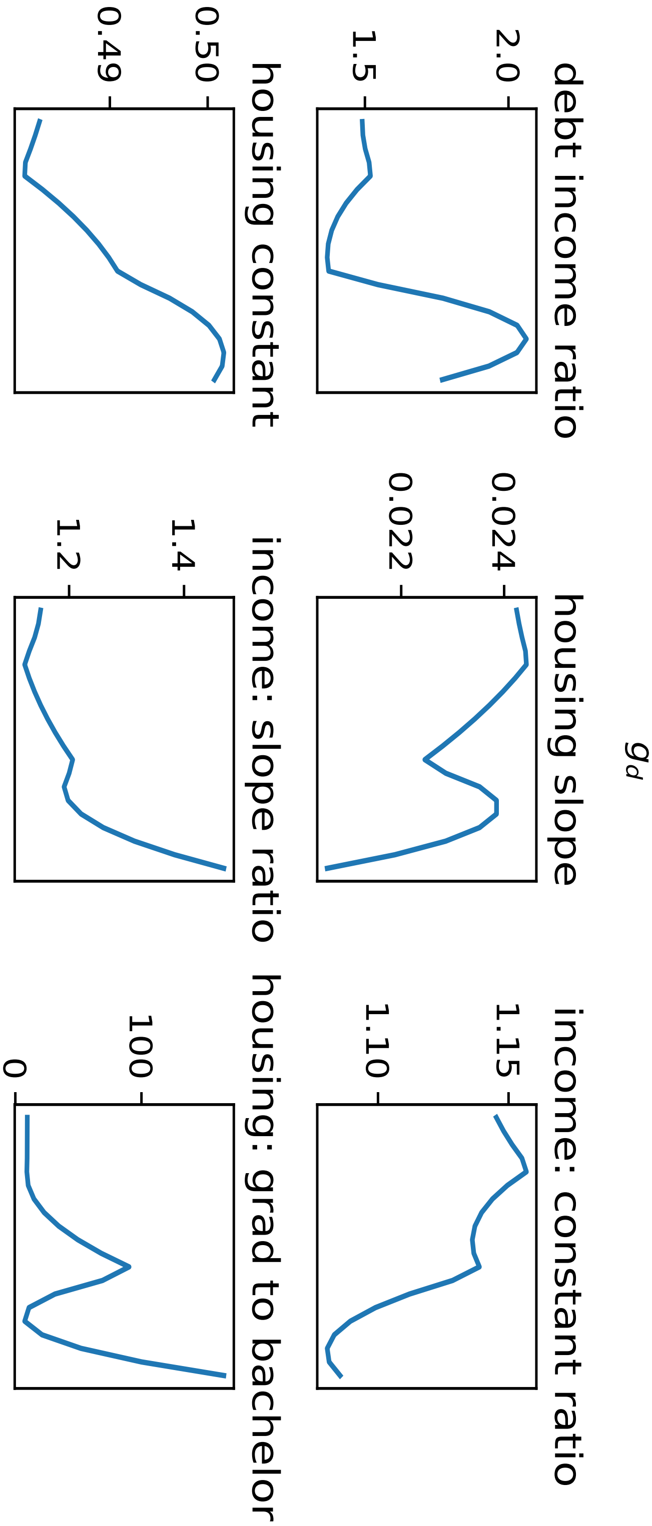

ζ₁
debt income ratio
1.5
1.0
0.5
housing slope
0.0250
0.0248
0.0246
income: constant ratio
1.8
1.6
1.4
1.2
housing constant
0.480
0.475
0.470
0.465
income: slope ratio
1.1
1.0
0.9
housing: grad to bachelor
200
100
0



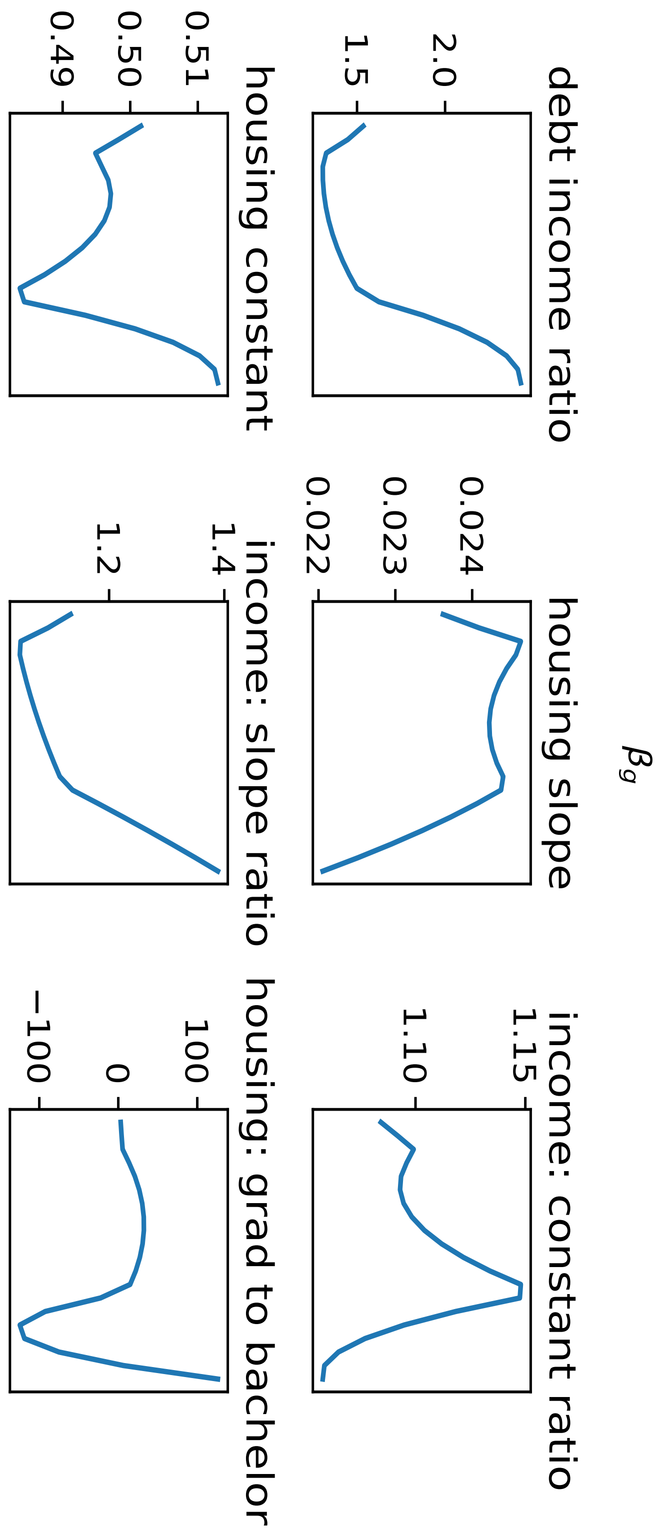
ζ_2
debt income ratio
housing slope
income: constant ratio
housing constant
income: slope ratio
housing: grad to bachelor
2.5
2.0
1.5
0.52
0.50
0.024
0.022
1.4
1.2
1.15
1.10
1.05
400
200
0



ξ
debt income ratio
1.4
1.2
housing slope
0.024
0.022
income: constant ratio
1.14
1.12
housing constant
0.490
0.485
income: slope ratio
1.3
1.2
housing: grad to bachelor
2000
1000
0

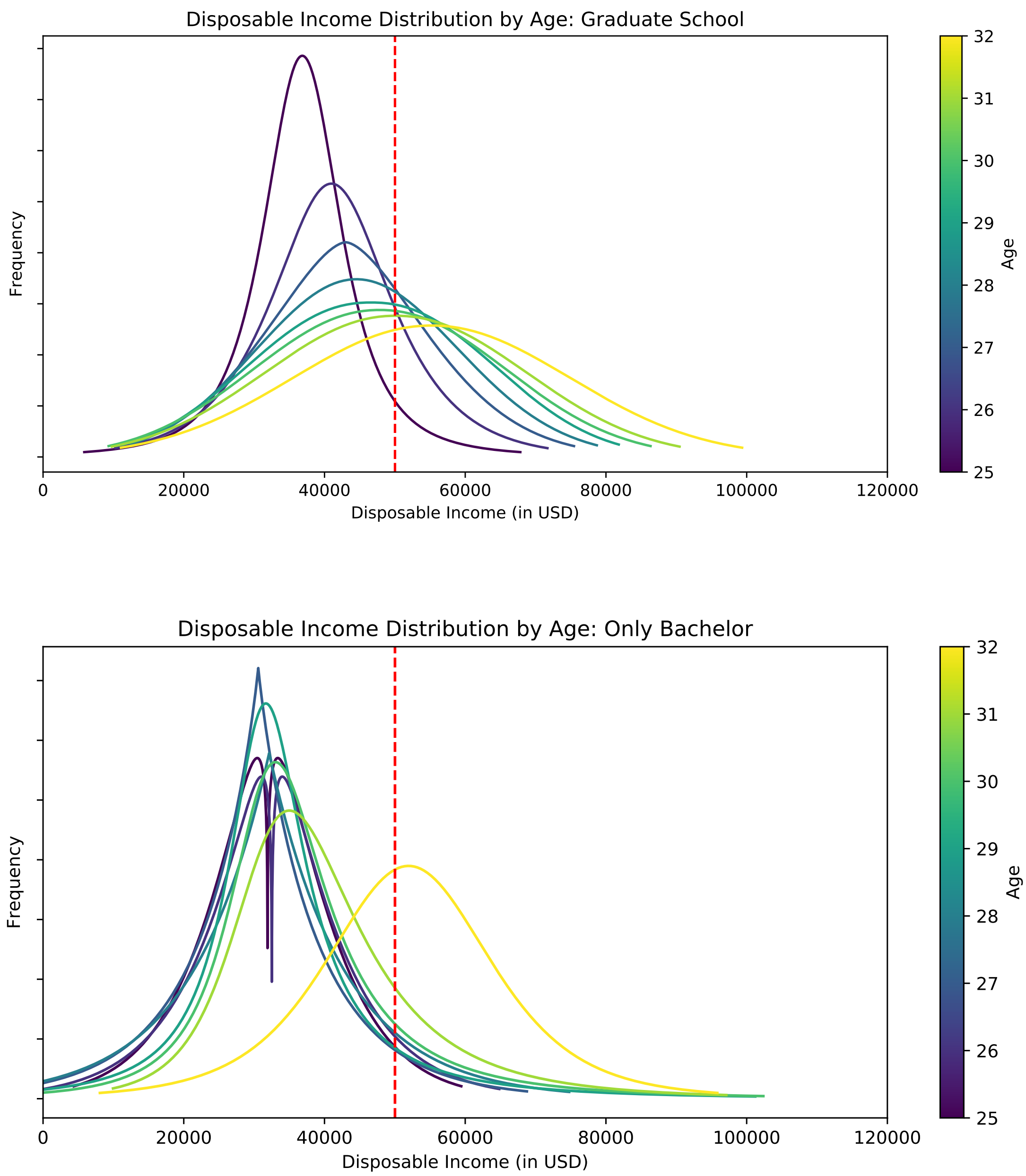


g_d
debt income ratio
2.0
1.5
housing slope
0.024
0.022
income: constant ratio
1.15
1.10
housing constant
0.50
0.49
income: slope ratio
1.4
1.2
housing: grad to bachelor
100
0


debt income ratio
housing slope
income: constant ratio
housing constant
income: slope ratio
housing: grad to bachelor
β_g
2.0
1.5
0.024
0.023
0.022
1.15
1.10
0.51
0.50
0.49
1.4
1.2
100
0
−100

Appendix 8. Additional Figures

Figure A2: Graduate School Educated Workers and Downpayment Constraint



Distribution of yearly disposable income, i.e. labor wages plus net liquid asset holdings, minus debt payments and housing expenditures for workers with graduate school education. The red line represents the downpayment constraint

Figure A3: Ratio of Student Loan Debt to Income, All Workers

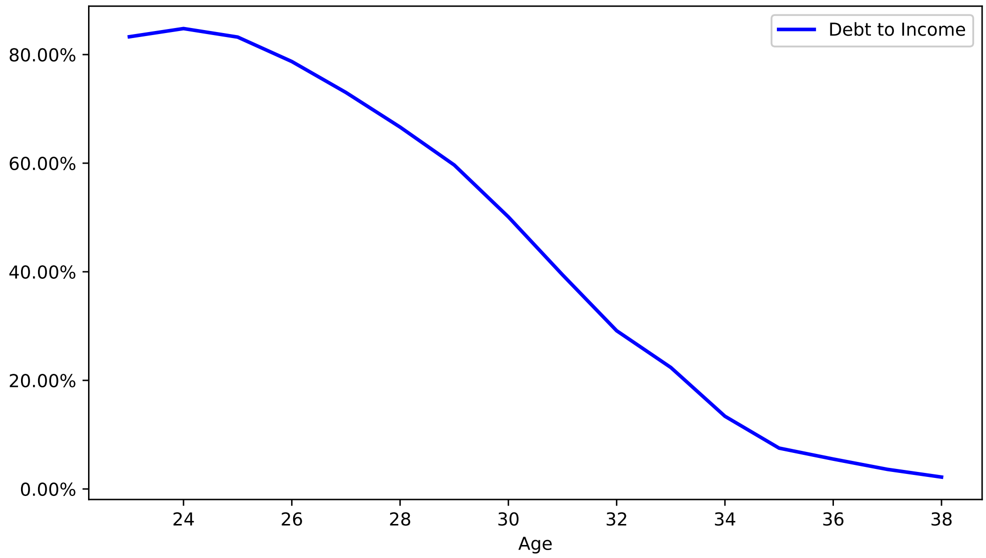
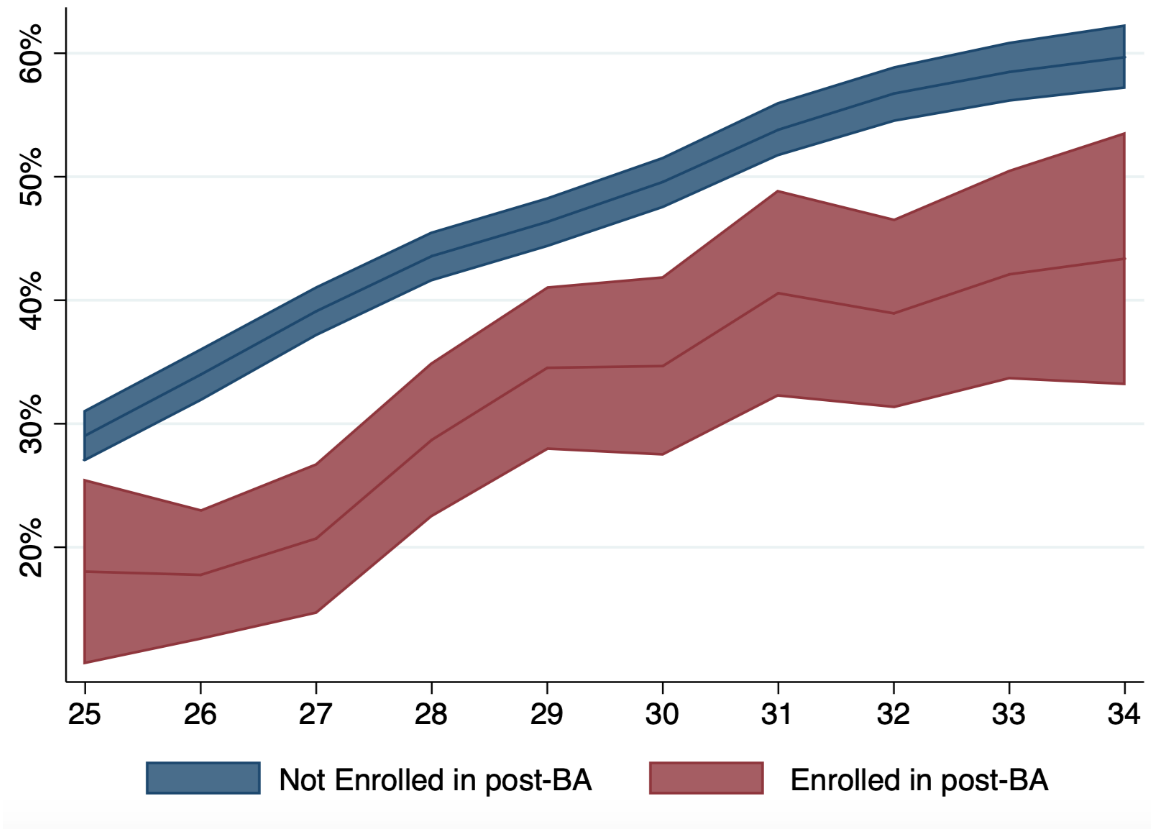


Figure A4: Entry into Home-Ownership by Education



Data: Current Population Survey for workers aged 25-34, years 2000-2018