Student Debt and Initial Labor Market Decisions:
Search, Wages and Job Satisfaction*

Mi Luo, Simon Mongey
New York University, New York University
March 14, 2016

Abstract

How does college debt - and financial wealth more generally - affect the labor market decisions of college graduates? Using rich restricted-use longitudinal data on a representative sample of college students we answer this question in two steps. First, via an instrumental variables scheme, we estimate that higher college debt causes individuals to take jobs with (i) higher wages, (ii) lower job satisfaction, and (iii) induces more on-the-job search. We prove that this behavior is rationalized by a McCall (1970) search model with asset accumulation and both wage and non-wage features of jobs: lower assets tilt the reservation wage-satisfaction locus. Second, we extended this model to a rich quantitative model, using the new dimensions of our data to estimate parameters by indirect inference. We first show that job satisfaction has a quantitatively large impact on individual decisions, and a move from low to high satisfaction positions is valued at between 2-6% of lifetime consumption. Since student debt repayment policies are exogenous, we estimate the model on students without student debt and show that the model successfully replicates behavior of students with debt. We conduct a number of policy-relevant counterfactual policy experiments. A key finding is that a transition to an income-based repayment policy (as used in other countries and proposed for the U.S.) is (i) preferred by low debt students, (ii) is welfare neutral when averaged over the current distribution of student debt. Finally, our model and data caution against computing welfare using just wages: job satisfaction is a quantitatively important consideration.

JEL: E21, H31, I22, J32, J33, J64
Keywords: Student debt, college education, labor, search, job satisfaction.

*Corresponding author: simon.mongey@nyu.edu, 19 W 4th St, New York City, NY 10012. We thank Katka Borovickova, Jarda Borovicka, Zvi Eckstein, Bob Hall, Oleg Itskhoki, Greg Kaplan, John Kennan, Phillip Kircher, David Laibson, Tom Sargent, Kevin Thom, and Gianluca Violante for useful comments and suggestions. We also thank seminar participants at the NYU Macroeconomics Student Lunch.
1 Introduction

Why is it important to understand how student debt affects the initial labor market decisions of college graduates? First, both student debt per borrower and the total number of borrowers increased by around 70 percent between 1997 and 2013, leading to a tripling of the outstanding stock of student debt, while the share of graduates from public (private) colleges with student debt has increased from 33 (45) to 64 (79) percent (see Figure 1, for a range of similar figures see Lee et al. (2014)). Second, recent papers have shown that initial labor market experiences can have strong effects on long term outcomes for wages and employment (Oreopoulos et al., 2012). We show that an important and missing dimension of the discussion to date is the debt-induced trade-off between wages and job satisfaction, that this is empirically meaningful and in an estimated model can have large implications for not just the magnitude of welfare responses to policy changes but also the direction. Policies that lead to higher wages may be associated with offsetting declines in non-wage utility.

Figure 1: Increases in U.S. student debt: 1997-2013

Notes (i) Data are taken from Yannelis (2015) Table 2. The data source is a 0.1% sample of the NLDS. (ii) Panel B - Data in Yannelis (2015) are not inflation adjusted, we plot 2013 inflation adjusted dollars using the CPI (All Goods). (iii) The data for public and private institutions are correctly specified in terms of the year of courses offered, however the For Profit designation cannot be broken down by year therefore For Profit in Panel B should be treated carefully since debt is the stock of debt on graduation. The increase could be due to changes in the composition of For Profit colleges, moving from two to four year colleges.

In this paper we use a rich new source of individual level data to describe the effect of debt on labor market outcomes and behavior. Unlike previous studies that consider student debt in the population of adult US households, this data allows us to focus on recent graduates for a clear picture of the effect of debt on individual decisions. We show that (i) within both part-time and full-time worker groups the probability of on-the-job search increases with student debt and is 20 ppt higher for students in the top quintile of borrowing than those in the bottom, (ii) this relationship is more pronounced over debt-to-income quintiles - since search increases with lower incomes - with a 35 ppt increase, (iii) within income terciles of full-time workers, those in the top debt quintile are around 15 ppt less likely to be satisfied with the non-pay related parts of their job than those in the bottom, and this inverse relationship is strongest in the lowest income tercile.

1 As noted by Lee et al. (2014), since 2009 the stock of student debt has surpassed all other forms of non-mortgage on household balance sheets and was the only form of non-mortgage debt for which households did not deleverage over the Great Recession.
Having established this set of correlations we proceed to further leverage our data to identify a causal effect of college debt on wages, job satisfaction and search. Identification is problematic due to the possible endogeneity of student debt. Consider the effect of debt on wages. On one hand unobserved backward-looking state variables relating to a lack of funding for college may be negatively correlated with ability and drive debt higher and wages lower. On the other hand unobserved forward looking state variables relating to career expectations may lead to high debt in anticipation of high wages. To address this we link our individual-level data to publicly available college-level data and use college level policy variables as instruments. We exploit across-time, within-institution changes in grant and loan policies as an exogenous source of variation in student debt, while also controlling for a wide range of observables and college selection on the basis of aid. We confirm our initial findings: higher student debt causes graduates to take jobs with higher wages, lower job satisfaction and to have a higher likelihood of search conditional on employment.

To understand how increases in debt induce a trade-off between wages and job-satisfaction we provide a simple theoretical framework. We adapt a McCall (1970) sequential search model to accommodate asset accumulation (as in Lise, 2013) and a non-pecuniary dimension to jobs that we call job-satisfaction. Under general conditions on preferences and the distribution of job offers we prove that the worker’s job acceptance policy takes the form of a reservation wage-satisfaction locus and that lower assets lead this locus to rotate toward accepting higher wage, lower satisfaction jobs. We point out that these theoretical findings apply very generally - not just to college graduates - and in this sense the simple theoretical model presents a teachable exercise that captures the non-pecuniary forces in Dey and Flinn (2008), Guler et al. (2012) and Mueller and Hall (2013).

In order to use the model for policy analysis and measuring outcomes we expand the simple model to include costly on-the-job search, borrowing constraints, and a rich institutional description of the repayment policies associated with student debt. The model is estimated by indirect inference on data in which unemployment durations, student loans, debt, on-the-job search, employment status, wages and job satisfaction are all observed. This allows for a precise quantification of the various frictions in the model. Since the parameters pertaining to student debt are entirely institutional we estimate the model using non-debt individuals and then test the performance of the model in capturing the behavior of those with student debt. The model is found to perform well and implies the same correlations captured in our empirical exercises.

Using the estimated model we show that the incorporation of non-wage aspects of jobs is important for evaluating the welfare consequences of proposed changes to repayment policies. We consider a policy change which was enacted in 2011, after our data; the introduction of an Income Based Repayment (IBR) plan. Under an IBR students only repay debt when employed and then only proportional to their income. The idea being that the repayment of debt is moved further into the future when wages are higher but possibly incurring larger total interest payments.\textsuperscript{2} We examine the effect of the policy on delinquencies, defaults and labor market outcomes for our sample cohort with four main results. First, keeping fixed the distributions of debt among graduates and available jobs, this policy leads to a neutral effect on average student welfare. Those with low debt prefer the fixed-repayment system and those with high debt prefer an IBR. However, contrary to popular reports that highlight high levels of individual debt, the average student debt is around $20,000, leading to these gains and losses netting out to zero. We find that a median voter would prefer the IBR. Second, although mean wages fall, graduates are no longer inclined to take up low job satisfaction positions in order to repay debt.

\textsuperscript{2}This policy was discussed in Kaplan (2008) and is the dominant repayment scheme in the United Kingdom, Australia, New Zealand and Singapore.
The rest of the paper is organized as follows. In section 2 we review the relevant literature. In section 3 we introduce the data used in our study and compare it to that used in existing work. Sections 4 and 5 provide our main empirical results and the identification strategy used in estimation. Section 6 develops a simple theoretical model with features that rationalize our empirical finding. This model is extended to a quantitative framework in 7 and estimated in section 8. In sections 9, 10 and 11 we examine how student debt affects behavior in the model, compare our results to the data, and conduct our repayment schemes policy experiments. Section 14 concludes.

2 Literature

2.1 Empirical

Descriptive studies of student debt

Despite its prominent position in policy discussion few papers have described, let alone established, the effect of higher student debt on individual behavior. A recent paper by Lee et al. (2014) uses repeated cross-sectional survey data on representative samples of adult US households to establish a set of cross-sectional and time-series features of student debt. On debt itself, one simple contribution of our paper is to compute statistics that relate to student debt using data on recently graduated students. The stark difference between these two data sources is shown in Figure 2 and will be discussed later.

Student debt and labor market outcomes

A number of papers have attempted to identify the effect of student debt on labor market outcomes using both event studies and estimated models of student debt, college participation and labor supply.

The work of Rothstein and Rouse (2011) is closest to ours in terms of identification strategy. Studying a single university, the authors exploit the exogenous variation in debt generated by the introduction of a no-loan policy under which the loan component of financial aid awards was replaced with grants. This quasi-natural-experiment is used to identify the causal effect of student debts on employment outcomes. Debt is found to cause graduates to choose substantially higher salary jobs and to reduce the probability that students choose low-paid “public interest” jobs. The authors find suggestive evidence that the behavior of students is more compatible with decisions made under credit constraints rather than preferences that include debt aversion. Rothstein and Rouse (2011) focuses on a single highly selective university. We find that a version of these results generalizes to the cross-section of U.S. colleges.

Joensen and Mattana (2014) provide a rich model of student debt and college participation which is estimated on the 2011 Swedish Study Aid Reform data. A transition from a loan-only policy to a grant-loan mix is found to not affect student behavior as long as there remains more weight on loans. When there is substantially higher weights on grants, however, more students graduate but stay enrolled longer. The results are unlikely to extend to the US due to a key difference in the funding of college education: Swedish college tuition is free to all students and loans are only for living expenses. Besides this the requirements on the data to identify the model parameters, specifically the panel requirement on individuals, exceed that which is available in the US.

Finally, our study is motivated by Oreopoulos et al. (2012) finding that early labor market outcomes can persist for many years into an individual’s career. Graduating in a typical recession - a rise in unemployment rates by 5 percentage points - is found to imply an initial earnings loss of about 9 percent that halves within
five years, and negligible by ten.

To the best of our knowledge the only other paper to use the NCES data on the student level is a working paper by Altonji et al. (2014). Their question and empirical findings are different to that pursued here. The authors combine numerous data sets to study the effect of poor labor market conditions on early careers, focusing on the variation of this effect across college majors. When majors are pooled they replicate the findings of Oreopoulos et al. (2012). Disaggregating by major reveals that in recessions, historically high-earning majors are sheltered; experiencing significantly smaller disadvantages in most labor market outcomes relative to average-earning majors.

A few very recent papers utilize NCES institution level data (IPEDS which we discuss later), in particular Liu (2015) and Yu (2015). The former studies the impacts of student loan policies on college outcomes and lifetime earnings, while the latter looks at college choices and the consequences of regulating for-profit colleges. Moreover, Wang (2015) uses the After the JD dataset constructed by the American Bar Foundation and the National Association for Law Placement, to study the impacts of student debts on the education, career, and marriage choices of female lawyers. We will have more to say about the relationship between our paper and these works in later versions.

2.2 Theoretical

The theoretical section of the paper contributes to two existing strands of the literature: (i) search with asset accumulation and, (ii) search when jobs are valued for both wage and non-wage features.

Search with asset accumulation

A recent but small literature studies on-the-job search under asset accumulation. We build on Lise (2013) in which a canonical McCall (1970) model with on-the-job search and stochastic job loss is extended to allow for savings in a risk-free bond. The author assesses whether the precautionary saving motive induced by unemployment in the presence of frictional labor markets can help explain the observed distribution of savings. When costly search effort is a choice - as in Pissarides (2000) - a positive correlation arises between assets and unemployment durations. Estimated on US worker data, the induced precautionary saving motive is shown to replicate the observed wealth, income and consumption distributions.

In an equilibrium model with voluntary quits into unemployment Rendon (2006) shows that higher initial wealth and access to larger amounts of credit increase both wages and unemployment duration. Employed workers accumulate wealth to finance quits into unemployment states where search for better jobs is more effective. We prove that - abstracting from quits - this negative correlation of reservation wages and assets can be achieved by the introduction of a non-pecuniary dimension to jobs. This will be consistent with our empirical finding that higher debt leads to higher wages and lower job satisfaction.

A recent paper by Kekre (2016) also builds a general equilibrium search model with search and matching frictions, incomplete markets and asset accumulation to study the interaction of unemployment insurance and aggregate demand. In his model market incompleteness with respect to unemployment risk generates an efficient role for the public provision of unemployment insurance.

Search with non-wage utility

We add to a growing literature that considers non-wage dimensions of jobs and how this may resolve some well known puzzles in the labor search literature. Hornstein et al. (2011) show that the standard McCall
model and a range of other canonical labor-search models quantitatively fail at matching the mean duration of unemployment conditional on (i) the observed distribution of accepted wages, (ii) a positive flow value of unemployment, (iii) the observed job-finding rate: the distribution is too narrow so the incentive to search too low. In a quantitative exercise Mueller and Hall (2013) add a non-wage utility to jobs with a dispersion calibrated to account for the observed acceptance (rejection) of offers below (above) stated reservation wages found in their survey data. This intuitively resolves the puzzle in Hornstein et al. (2011) but requires a negative correlation between wages and non-wage utility, inducing longer unemployment durations. Unlike Mueller and Hall (2013) we use measurements of job satisfaction and estimate a positive correlation in the underlying wage-satisfaction offer distribution. However with on-the-job search we are still able to match search durations under positive unemployment flow utility in a version of the model without on-the-job search.

A similar logic lies behind the results of Dey and Flinn (2008) and Guler et al. (2012). In the former, health insurance to one employed spouse provides non-wage utility to the searching spouse, increasing reservation wages for any given distribution of wage offers. In the latter, spousal employment provides non-wage utility to the searching spouse again lengthening unemployment durations for any given distribution of wage offers. Our quantitative exercise uses data on unemployment durations, accepted wages, job satisfaction and on-the-job search behavior to calibrate our model, allowing us to contribute to and combine both of the above theoretical discussions: How do (i) debt and (ii) non-wage utilities affect job search behavior?

3 Data and characterizing student debt

Student-level data

The main data source we use throughout our study is restricted-use micro-data from the National Center for Education Statistics (NCES) Baccalaureate and Beyond (BB) surveys.

The surveys are repeated cross-sectional surveys of a nationally representative sample of post-completion undergraduate students. A single wave of the survey consists of individual responses to questions at a number of points in time: the last year of study, a year after graduation and ten years after graduation. The conduct of these follow-up surveys is irregular leading us to focus on early labor market outcomes over the first year after graduation. Surveys are available for the graduating classes of 1993, 2000 and 2008. We focus on the latter two cohorts (BB00, BB08) since student debt is negligible in the first cohort. Questions are consistent across surveys and span a wide array of topics including labor market outcomes, debt, search behavior, job satisfaction, demographics and parental background. An appealing feature of the data is that a number of data are not self-reported; (i) academic results such as SAT scores and GPA are taken from administrative records, (ii) student loan borrowing, grants received, parental income and tuition costs are taken from Federal and college records, and (iii) income is taken from IRS data.

Since the data consider unconventional measures usually not available to labor economists we replicate the precise questions that generate the data when we think the underlying question may be unclear from its description in the main text. See Appendix B.
Institution-level data

Through unique college identifiers in BB00 and BB08 we are able to link the student-level data to publicly available institution level data. We use two sources. The first is another NCES data-set taken from the Integrated Post-secondary Education Data System (IPEDS). These annual data cover the universe of post-secondary institutions that participate in the federal student financial aid program (Title IV program) and provides information on the total number of students in the university, the type of university (public, private, for profit, non-profit). Importantly for our identification scheme the data includes information on the financing of student tuition and expenses within the entire undergraduate population. For example data on the number and total value of institutional grants, federal grants, Stafford loans, and Pell grants are provided for all institutions from 1999 onwards.\(^5\)

The second data set is the recently released College Scorecard data (CSC). Also publicly available, the CSC covers the universe of institutions participating in Title IV lending from 1996 to 2014. The data is an amalgam of data from IPEDS, Treasury and the National Student Aid Study (NSAS). A rich set of college quality measures are available in this data including the inputs (e.g. the 10th, 50th and 90th percentiles of SAT scores of the entering cohort) and outputs (e.g. average wages at regular intervals after graduation). Additionally the data include measures of default and delinquency at regular intervals after graduation by loan (e.g. fraction of borrowers in default on Stafford loans). We have already used this data in producing Figure 1.

3.1 Distribution of student debt

Our study compliments the already discussed work of Lee et al. (2014) in which student debt is considered in all adult households. A drawback of the empirical results of that paper is that they do not lend themselves to statements regarding the student debt of graduating students. Similarly restrictive is an analysis involving the sticker prices of degrees (as used in estimation by Kenman, 2011). Although information on sticker prices of degrees are widely available they do not map neatly into graduating student debt due to the availability of grants, loans and additional expenses.

In Figure 2 we use our data to make both of these points clear. Figure 3a shows how the distribution of student debt in a graduating cohort differs from the distribution in the population of all individuals with positive student debt. Given repayments and aging, debt in the adult population has an exponential-like distribution, while upon graduation there is significantly fewer students with small measures of debt.\(^6\) Figure 3b demonstrates that student debt and tuition vary greatly. In particular over 20 percent of students take out debt that exceeds tuition, speaking to the importance of considering other expenses, while the 80 percent that take out loans less than the value of tuition must necessarily have support by other means. Our data allows us to separate these different sources of finances and costs both at the individual and institutional level.

---

\(^5\) A subtle timing issue arises. The university wide information regards the population whereas the student-level information is based on individual graduating cohorts. Ideally we would consider data on the graduating cohort as population wide statistics may reflect policies that have been enacted since the surrey cohort began studying but did not effect that cohort. This is exacerbated by the surveys being 3-4 years apart. Since the IPEDS data is annual we are able to test how university policies change during a student’s time in college. For more information on IPEDS see: http://nces.ed.gov/ipeds/about/

\(^6\) The comparison is less useful at the top end of the distribution since the BB01/8 data miss the right-tail generated by post-graduate student debt.
3.2 Sample selection

Summary statistics for the full sample without any conditioning are available in Appendix A Table 5. Before we move on to any detailed analysis, we carry out several steps of cleaning to get to a workable sample. First, we keep only those with age no more than 30 years old. Second, we drop those graduates who reportedly went to more than one college. Our instruments are on the institutional level, so we require that each student only goes to one school. Finally, we keep only four-year institutions and count the number of graduates in each institution sampled in the BB00 and BB08, respectively, and keep only those institutions with at least three graduates in both cohorts. In the actual regression exercises, we further condition on the full-time status (working more than 39 hours weekly). The remaining sample size for the regression sample of two cohorts is 2,558 together. We also look at the subsample with positive debts and compare results with the baseline.

4 Empirical

We first consider raw correlations between student debts and labor market behavior and outcomes using the BB08 data only. While these are pure correlations in the cross-section, some reasonable conditioning allows us to derive some noteworthy patterns that we will return to with our model. In Appendix E we provide some further interesting empirical facts regarding (i) debt levels and parental income, and (ii) distribution of debt to income across institution types.\(^7\)

---

\(^7\)These provide more background for the reader, further fleshing out the data, however are less directly related to the study at hand so placed in an appendix.
Figure 3: Effect of student debt on employment plans

Notes (i) The question asked is “Has the amount of student loan debt you have from your undergraduate education influenced your employment plans and decisions in any way?”, (ii) Debt quintiles are computed within parental income quantiles, (iii) Residual debt is the estimated residual $e_i$ from a regression of $\log d_{i,j} = \beta' X_i + e_i$ where $X_i$ includes age, gender, race, SAT score and school dummies.

1. Employment decisions

As a first pass we consider the relationship between student debts and subjective evaluation of whether the graduate’s job decisions have been influenced by the debts. Our data includes a binary question asking all the debt holders whether they think their job decisions have been influenced by student debts in any way. The exact question reads: “Has the amount of student loan debt you have from your undergraduate education influenced your employment plans and decisions in any way?” Figure 3 plots the fraction of respondents answering yes to this question against borrowing quintiles. We plot these means separately for people with parental income below and above the median. The left panel uses the actual debt level for defining the quintiles on the horizontal axis, while the right uses the residual debt $\hat{e}_i$ from the following regression:

$$\log d_{i,j} = \gamma_j + \beta' X_i + e_{i,c}$$

where $X_i$ includes age, gender, race, GPA and school dummies for individual $i$. Both panels display a positive correlation between student debt and the (subjective take on whether) influence of debt on labor market behavior. The smaller slope in the second panel suggests that co-variates in $X_i$ are positively related to the answer to the survey question. We view these simple results as prima-facie evidence of the effect of debt on labor market behavior, we now consider on what dimensions this may play out.

2. Job satisfaction

Next we consider direct measures of job satisfaction. The BB01 and BB08 questionnaires ask a set of binary questions regarding satisfaction with pay, job security, career fit, major relevance, importance in the workplace, and overall satisfaction. Figure 4 plots the fraction of full-time individuals reporting they are satisfied by debt quintile. The left panel considers only the question regarding satisfaction with pay, while the right plots a measure of the fraction that report an answer of satisfied to all of the non-pay related questions. We will later use this measure in estimation of our quantitative model. Since income and job-satisfaction are
highly correlated we split the sample into income terciles and compute debt quartiles within each income tercile. The main results is that job satisfaction with both pay and non-pay related features of work are clearly declining by debt within each income group.\(^8\)

### 3. On-the-job search

Here the binary question we consider asks employed individuals “Are you currently looking for a job?”. Figure 5 plots the fraction searching within debt quintile bins (left panel) and debt-to-income quintile bins (right panel).\(^9\) The zero on the x-axis corresponds to those with zero student debt, which comprise 23 percent of the sample. We find a clear a positive correlation between both debt holdings and debt-to-income ratios and rates of on-the-job search. The steeper relationship in Panel B is due to higher search at lower incomes. Clearly search is also strongly effected by job satisfaction, the average rate of search among less satisfied workers is over 30 ppt higher than high satisfaction workers. Supposing that all workers draw from the same distributions of jobs and costly search, these results point to higher debt workers placing a lower value on jobs at all wage and satisfaction levels.

### 5 Empirical - Instrumental variables estimation

We proceed to estimate the causal effect of student debt on initial labor market choices, in particular search, income and job satisfaction. We find that higher student debts cause graduates to take on jobs characterized by relatively higher salaries, lower job satisfaction, and have a higher probability of on-the-job search, lower probability of taking a teaching position, and lower probability of relevance of their major studied to their

---

\(^8\)One thing to point out: while pure satisfaction measures can be criticized about the vignette effect, i.e. people with more debts could be viewing everything with lower satisfaction so we need some anchoring, the search variable here suffers less from this issue. People who search more intensively on the job are likely to be those who are genuinely less satisfied with the job itself. 

\(^9\)As further evidence of the meaningfulness of the survey measure of search, we find that search is 6 ppt higher among part-time workers.
Figure 5: Student debt and on-the-job search for full- and part-time workers

Notes (i) The question asked is “Are you currently looking for a job?”; (ii) Zero on the x-axis corresponds to students with zero debt (23% of the sample); (iii) Part-time workers are those workers that are employed and report average hours of less than 35 per week; (iv) Income is measured as annual income and debt is cumulative student borrowing upon graduation; (v) Since all unemployed workers search by definition we limit the figure to employed workers only.

current job.

Estimating equation The model we are interested in estimating is given by the following equation

\[ y_{i,j,c} = \alpha + \beta D_{i,j,c} + \Gamma X_{i,j,c} + \lambda_c + \gamma_j + \varepsilon_{i,j,c} \]  

(1)

where \( y_{i,j,c} \) is a measure of an outcome for an individual \( i \) of cohort \( c \) that attended college \( j \). These outcomes depend on the level of student debt \( D_{i,j,c} \), a vector of individual-level observables \( X_{i,j,c} \), the individual’s graduating cohort \( \lambda_c \), institution-level dummy \( \gamma_j \) and an unobserved component \( \varepsilon_{i,j,c} \). We seek an unbiased and consistent estimate of the parameter \( \beta \).

Sample selection We use data from the BB00/8. The sample is restricted to individuals that at the time of interview report (i) under the age of 30 on graduation, (ii) work full time (more than 39 hours weekly), and (iii) having attended only one institution. We consider only four-year colleges. After imposing these restrictions we remove all colleges for which we do not have more than 3 observations in both waves.

Controls and measurement Debt \( D_{i,j,c} \) is measured as cumulative borrowing upon graduation, a statistic which has been cross-referenced against institutional and federal records by the NCES.\(^{10}\) The vector of observables \( X_i \) includes individual level controls pre-determined before college: gender, taking Advanced Placement (AP) courses in high school, a quadratic in age, dummies for race (white, black, Asian and other). We consider a number of dependent variables. Our measurement for income is annual salary including wages and compensations. Job satisfaction is either a binary variable for general satisfaction, or an average for a composite of questions related to job satisfaction in the survey as used in Figure 4. Specifically, we are

\(^{10}\)The amount borrowed is checked against institutional records as opposed to the amount owing upon graduation which is not. So despite the latter is arguably a more relevant measure when considering labor market decisions we prefer amount borrowed. Robustness checks show that this decision does not substantially change our findings.
interested in satisfaction about pay, job security, career fit, major relevance, importance in the work-place.

5.1 Identification

There is a clear endogeneity issue in estimating equation (1) by OLS. In particular, debt decisions at both the intensive and extensive margins are subject to unobserved individual factors that may also affect labor market outcomes. That is $E[D_{i,j,c} \varepsilon_{i,j,c}] \neq 0$. For example, high ability individuals may take on higher debts given their forecast of higher wages. On the other hand, low ability individuals may have low ability parents with limited resources, leading to high amounts of debt but wages that are low reflecting their ability. A priori we have no grounds to expect either of these biases to dominate.

The rich structure of our data allow us to incorporate several remedies: ability is captured imperfectly by high-school AP credit, and the correlation between institution, wage and debt is captured by institution-level controls or fixed effects. However we seek a more reliable source of exogenous variation in debt, independent of unobserved factors such as ability.

Motivated by Rothstein and Rouse (2011) we choose an instrument that depends on college policy. In particular, we take as our instrument $Z_{j,c}$ the ratio of total institutional grants to total institutional loans in college $j$ for cohort $c$, and exploit its variation across cohorts, within an institution

$$Z_{j,c} = \frac{\text{Grant}_{j,c}}{\text{Grant}_{j,c} + \text{Loan}_{j,c}} \in [0, 1]$$

As opposed to loans, grants do not have to be repaid. We therefore claim that a decrease in this variable exogenously causes an increase in the level of debt of students in cohort $c$ relative to the debt of previous cohorts. We can identify $\beta$ under the exclusion and relevance conditions $E[Z_{j,c} \varepsilon_{i,j,c}] = 0$ and $E[Z_{j,c} D_{i,j,c}] \neq 0$. Note that the measurements of $\text{Grant}_{j,c}$ and $\text{Loan}_{j,c}$ do not rely on the BB01/8 samples since IPEDS contains university level data for all years.\footnote{We set compute $Z_{j,c}$ for a cohort graduating in year $t$ using data on grants and loans from time $t-4$ given that the university policy in place when admitted tends to be binding over the student’s attendance at that university.} Whereas Rothstein and Rouse (2011) consider only a “highly selective university” (p. 149) our instrumental variable scheme, implementable with the BB00/8 data, allows us to extend the scope of study to a representative sample of college students.

We estimate the model by two stage least squares using data from two cohorts, therefore if we wish to separately identify college and cohort fixed effects it is important that there is significant within college variation in $Z_{j,c}$ over time. Figure 6 demonstrates that such variation exists. The left panel shows the positive correlation in $Z_{j,c}$ across cohorts, but there is still substantial variation. This is visualized by plotting a histogram of $\Delta_{c}Z_{j,c}$, as shown in the right panel.

The identifying assumption that is required so that the exclusion restriction $E[Z_{j,c} \varepsilon_{i,j,c}] = 0$ holds is that the grant / loan policies of colleges do not affect students’ college choices. Its straightforward to see why this selection issue would break identification. Suppose a student receives offers from two universities $j_1$ and $j_2$ with policies $Z_{j_1,c}$ and $Z_{j_2,c}$. If these policies effect the decision of $j_1, j_2 \in \{j_1, j_2\}$ in a way that is correlated with unobservable characteristics of the student that also effect debt and $y_{i,j,c}$ then clearly $E[Z_{j,c} \varepsilon_{i,j,c}] \neq 0$. Since we neither (i) have a panel of neighboring cohorts, (ii) observe the set of offers of enrollment and financial support, we cannot test this assumption in our scenario. We do make two points which we think are in our favor. First, we have introduced an almost unprecedented array of controls, a number of which are usually used themselves for instruments for some of the unobservables we may be worried about entering $\varepsilon_{i,j,c}$ such as ability and parental background. Second, as Rothstein and Rouse (2011) point out (p. 159) in
their robustness checks, excluding students who might have applied or enrolled as a result of the reform does not influence the magnitude or significance of their estimated effects on salaries. We hope that their result provides convincing evidence that college choices are not impacted by financial aid policies at the institution level but more by personal preference.\textsuperscript{12,13}

5.2 Results

Results from our estimation of equation (1) by 2SLS are given in Table 1 columns (1-6), and by OLS in columns (7-8).

Column (1) shows the effect of debt on log salaries. Increasing debts by $1,000 boosts salaries by 4.42\% on average for those with a full-time job. However, when we condition on the subsample of individuals with positive debts, a $1,000 increase in debts boosts salaries by 2.23\%. One standard deviation in loans ($16,644) among full-time graduates increases log of salaries by 1.466 standard deviation.

Columns (2-3) compare general job satisfaction and the satisfaction index excluding pay across individuals with different levels of debt. Increasing loans by one (conditional) standard deviation in the 2008 cohort ($16,644) decreases general satisfaction by 0.260 standard deviations. Again, under OLS (column 8), the coefficient on debt is insignificant and zero.

Column (4) considers whether individuals are searching on-the-job. A $1,000 increase in borrowing leads to a 0.93\% increase in the probability of on-the-job search. Column (5) considers whether the job is related to an individual’s major. A $1,000 increase in borrowing leads to a decrease in the probability of major relevance of 1.77\%. Columns (6) shows the effects on whether individuals have a teaching job. A teaching position is a good example of jobs with large public interests but average lower salaries, and the results show that debt burdens discourages people from choosing teaching jobs.

Column (7-8) shows that the coefficients on debt and search either close to zero or negative under OLS, indicating that OLS is biased \textit{downwards}. The most likely candidate for biasing in this direction is selection on ability.

\textsuperscript{12}In Appendix C we consider an extension of our quantitative model which, when estimated, will inform us as to the relative effects of college taste preferences and financial packages on college choice.

\textsuperscript{13}In Appendix D we consider additional robustness checks using \textit{College Score-card} data, focusing on measuring the effect of $Z_{j,c}$ on composition of grants, cohort quality (SAT scores) and background (forthcoming).
Table 1: Effects of student debts on initial labor market decisions: IV with 2000 and 2008 cohorts

<table>
<thead>
<tr>
<th>Variables</th>
<th>IV (2SLS)</th>
<th>OLS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>log(Salary)</td>
<td>Satisfaction</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>$D_{i,j,c}$</td>
<td>0.0442***</td>
<td>-0.0060</td>
</tr>
<tr>
<td></td>
<td>(0.01533)</td>
<td>(0.00690)</td>
</tr>
<tr>
<td>Male</td>
<td>0.2956***</td>
<td>0.0325*</td>
</tr>
<tr>
<td></td>
<td>(0.04527)</td>
<td>(0.01929)</td>
</tr>
<tr>
<td>GPA</td>
<td>0.0177</td>
<td>-0.0044</td>
</tr>
<tr>
<td></td>
<td>(0.01636)</td>
<td>(0.00734)</td>
</tr>
<tr>
<td>Age</td>
<td>-0.2039</td>
<td>0.0268</td>
</tr>
<tr>
<td></td>
<td>(0.23496)</td>
<td>(0.10695)</td>
</tr>
<tr>
<td>$Age^2$</td>
<td>0.0040</td>
<td>-0.0007</td>
</tr>
<tr>
<td></td>
<td>(0.00491)</td>
<td>(0.00224)</td>
</tr>
<tr>
<td>Constant</td>
<td>12.1712***</td>
<td>0.7088</td>
</tr>
<tr>
<td></td>
<td>(2.73409)</td>
<td>(1.23771)</td>
</tr>
<tr>
<td>Race dummies</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Inst. dummies</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Cohort dummies</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>2,545</td>
<td>2,506</td>
</tr>
</tbody>
</table>

Note (i) Standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. (ii) The dependent variables for column’s (2), (4), (5), (6) are indicators taking the value of 0 or 1. (iii) Salary is annual earnings, (iv) Estimated on full-time students under 30 in four-year colleges.

6 Basic theoretical framework

In this section we present a simple extension of the Lise (2013) partial equilibrium labor-search model that is able to accommodate our empirical findings: increases in student debt induce a trade-off between wages and job satisfaction. In the Section 7 we extend this model to allow for realistic (i) student-debt repayment rules, (ii) on-the-job search, and (iii) borrowing constraints and to show how changes in these features effect this trade-off.

6.1 Environment

Time is discrete. Workers are infinitely lived and discount the future at rate $\beta$. Each period a worker may be either employed or unemployed. Agents maximize lifetime utility which is time separable with period utility given by the function $U(c, \psi) = u(c) - E_t v(\psi)$ which depends on consumption $c$ and, when employed ($1_{E_t} = 1$), the non-wage utility of the job $\psi$

$$\bar{U} = \sum_{t=0}^{\infty} \beta^t [u(c_t) - 1_{E_t} v(\psi_t)].$$

We assume that both $u$ and $v$ are continuous, positive and twice continuously differentiable with $u', -u' > 0$ and $u'', -v'' < 0$. Workers hold assets $a$ which earn a risk-free rate of return $r < \beta^{-1} - 1$. In both employment states the worker chooses consumption and savings, with income being equal to a constant level of benefits $b$ when unemployed and a wage $w$ when employed. Workers may borrow and face an exogenous borrowing limit $\Gamma \leq 0$. Jobs are heterogenous in the bundles of wage and non-wage utility provided to the worker $(w, \psi)$. The distribution of these jobs is given by the joint distribution function $F(w, \psi)$ with continuous
density $f(w, \psi)$ over a a bounded, connected supports $w \in W = [w, \bar{w}]$ and $\psi \in \Psi = [\psi, \bar{\psi}]$. Employed workers are separated into unemployment at the end of the period with probability $\delta$. Labor markets are frictional such that at the end of each period unemployed workers draw a job $(w, \psi) \sim F$ with probability $\lambda$. We assume and that the Inada conditions hold for both $u$ and $v$ on their domains.\footnote{Formally we assume that $\lim_{\psi \to \psi} v(\psi) = \infty$, $\lim_{\psi \to \bar{\psi}} v(\psi) = 0$ and $\lim_{c \to 0} u(c) = -\infty$.}

### 6.2 Worker’s problem

Let $U(a)$ be the present discounted value of lifetime utility of an unemployed worker holding assets $a$, before the possible realization of a draw of a job. Let $W(a, w, \psi)$ be the present discounted value of lifetime utility of an employed worker in a job $(w, \psi)$ holding assets $a$ at the beginning of the period before her consumption decision. These two values may be written recursively as follows

1. **Value of unemployment**

\[
U(a) = \max_c \left[ u(c) + \beta \lambda \int \max \{ W(a', w', \psi'), U(a') \} dF(w', \psi') + (1 - \lambda)U(a') \right] \\
\text{s.t.} \\
a' = (1 + r)a + b - c \\
a' \geq \Gamma
\]

2. **Value of employment**

\[
W(a, w, \psi) = \max_c \left[ u(c) - v(\psi) + \beta \delta U(a') + (1 - \delta)W(a', w, \psi) \right] \\
\text{s.t.} \\
a' = (1 + r)a + w - c \\
a' \geq \Gamma
\]

We prove that the model we have described can accommodate our findings by providing a reasonable characterization of the job-acceptance policy and its dependence on asset holdings without any further assumptions on the joint distribution of $w$ and $\psi$.

Standard dynamic program arguments give the existence, uniqueness and continuity of $W(a, w, \psi)$ and $U(a)$ in all arguments. The solution comprises value functions $W$ and $U$, consumption policy functions $c_U(a)$ and $c_E(a, w, \psi)$, and a job-acceptance policy $g(a', w', \psi') \in \{0, 1\}$. It can also be shown that the function $W(a, w, \psi)$ is increasing in both $w$ and $\psi$ for any $a$. In what follows we also assume that $F$ is such that $W$ is jointly concave in $(w, \psi)$.\footnote{Given the concavity of $u$ and $v$ this should be simple to prove, but the exact specification of $F$ provides some difficulty. If $F$ were uniform we would be able to prove concavity by standard arguments, establishing that the pair of Bellman equations represent a functional operator $T$ which is a contraction and then showing that $T$ maps concave functions into concave functions. However under a general $F$ we can’t be sure that the integral in (2) preserves concavity. We are working on what restrictions we may need to place on $F$. For a proof in a similar setting see Jarosch (2015).}

Since $U(a)$ is independent of $w$ and $\psi$ the policy $g$ takes the form of a reservation job policy of the form

\[
g(a, w, \psi) = \begin{cases} 
1, & \text{if } (w, \psi) \in \mathcal{A}(a) \\
0, & \text{if } (w, \psi) \in \bar{\mathcal{A}}(a) 
\end{cases}
\]
where the set of acceptable jobs \( \mathcal{A}(a) \) is defined by

\[
\mathcal{A}(a) = \{(w, \psi) \in W \times \Psi \mid W(a, w, \psi) \geq U(a)\}.
\]

We now provide five propositions that build towards a close characterization of the properties of the job-acceptance policy. Proofs are in Appendix F.

**Proposition 1.** There exists a continuous function \( h(a, \psi) \) such that for all \( (a, w, \psi) \), \( (w, \psi) \in \mathcal{A}(a) \) if and only if \( w > h(a, \psi) \). For any level of assets \( a \), the function \( h(a, \psi) \) is strictly decreasing and convex in \( \psi \).

**Proposition 2.** The derivative \( h_{\psi,a}(a, \psi) \) is negative, that is, as assets decrease the function \( h(a, \psi) \) becomes steeper. Also, for any decrease in assets \( a \) to \( a' < a \) there exists some \( \bar{\psi} \) such that \( h(a, \bar{\psi}) = h(a', \bar{\psi}) \) and for all \( \psi < \bar{\psi}, h(a', \psi) > h(a, \psi) \) while for all \( \psi > \bar{\psi}, h(a', \psi) < h(a, \psi) \).

**Corollary 3.** Let the population distribution \( F_{w,\psi}(w, \psi) \) be jointly uniform. Denote by \( F_t(a, w, \psi) \) the sampling distribution after \( t \) periods, initialized by a distribution of unemployed workers with initial asset distribution \( a_{i,0} \sim F_0(a) \). Then sample correlations measured from \( F^* \) have the properties (i) \( \text{cov}(a_0, w) < 0 \), \( \text{cov}(a_0, \psi) > 0 \), (ii) let \( a' > a \), then \( \mathbb{E}_{F_t}[w|a'] < \mathbb{E}_{F_t}[w|a] \) and \( \mathbb{E}_{F_t}[\psi|a'] > \mathbb{E}_{F_t}[\psi|a] \).

The properties of the job-acceptance policy described in Propositions 1-4 are shown in Figure 7. Essentially Proposition 4 establishes the existence of a substitution effect and a wealth effect. As assets decrease a substitution effect leads to a trade-off of higher wages for lower job satisfaction. However the worker’s decreased wealth leads them to accept both lower wage and lower satisfaction jobs since both are normal goods.

**Proposition 4.** The effect of an increase in debt on the job-finding rate of the worker is indeterminate without placing further assumptions on \( F \). Even under a uniform distribution the effect is indeterminate given the off-setting effects of a decrease in \( U(a) \) (accept more jobs) and an inwards rotation of \( h(a, \psi) \) (accept higher wage jobs, same \( \psi \) jobs, therefore less jobs).

We have shown that the Lise (2013) model extended to allow for non-wage utility can qualitatively generate the observed relationship between debt and job satisfaction that was the main result of section 5. We now extend the model and ask whether it can be identified from our empirical results, and if so, can an estimated version of the model generate the cross-sectional relationships between debt, wages, job satisfaction, and job finding rates which we have found in the data.

### 7 Quantitative model

We have shown that the baseline model can accommodate our empirical finding: decreasing levels of assets can generate a negative correlation between wages and job satisfaction. However the model does not contain features that distinguish student debt from other forms of debt, specifically its repayment requirements. We have also abstracted from on-the-job search behavior which we have shown to be strongly effected by levels of student debt. We now add these features to the model in a way that we can bring to the BB08 data.

Much of the structure of the simple model remains. The state vector \( s_F \) for an employed worker is \( s_F = (a, d, t, w, \psi) \) and contains liquid assets \( a \), outstanding student debt \( d \), time since graduation \( t \), wage \( w \) and job-satisfaction \( \psi \). For an unemployed worker the state vector \( s_U = (a, d, t) \). The initial state of the agent is unemployment with assets \( a_0 \in \mathbb{R} \), student debt \( d_0 \in \mathbb{R}_+ \), and \( t_0 = 1 \).
7.1 Environment

We aim to accurately model the repayment rules faced by student loan holders. To this end we introduce the following general objects which in later sections we specialize to replicate features of current and proposed policies.

Definition. A repayment policy $R$ is a tuple of functions $R = (\rho, \Delta, \tau)(s)$ specifying

1. The repayment function $\rho(s)$ specifies the full required repayment on the principal $d$ in the current period.

2. The penalty function $\Delta$ specifies the evolution of debt $d' = \Delta(d, w, t)$ if the loan repayment is not paid. This includes any penalties for late repayment and deferral policies that excuse penalties in the months following graduation.

3. The deferral function $\tau$ specifies the evolution of the date of the loan $t' = \tau(d, w, t)$ if the loan repayment is not paid. This captures renegotiation of the loan and other institutional features.

Additionally we assume that an individual is forced to make all repayments possible up to a consumption floor $c$.

We also make the following changes to the environment. Since standard repayment period for college debt is ten years it would be counterfactual to impose $a' \geq 0$ until debt is repaid. When the worker is employed we constrain $a' \geq -\gamma w =: \Gamma_E(s_E)$. An unemployed worker cannot extend their credit-lines any further and so faces the borrowing constraint $a' \geq \min \{a, 0\} =: \Gamma_U(s_U)$.\footnote{This implies that on graduation since $a = 0$ then the worker cannot borrow at all against their human capital.} We assume that the interest rate on student debt $r^d$ is constant and allow the rate of return on liquid assets $r^a(a)$ to potentially vary with the assets.

All unemployed workers search and face the same probability $\lambda_U$ of drawing from $F$. For employed workers we assume that search is costly in utility terms. At the convening of the labor market an employed
worker draws an iid utility cost of search $\kappa \sim H(\kappa)$, $\kappa \in [\underline{\kappa}, \bar{\kappa}]$. If the cost is paid an offer arrives with probability $\lambda_E$, if the cost is not paid then the the worker does not search. Random search costs serve two purposes (i) it introduces additional noise into the model allowing us to account for observations that would otherwise be probability zero under the model, (ii) it smooths the value functions allowing us to use sparse polynomial approximations even in the presence of kinks induced by the job acceptance decision.

### 7.2 Worker’s problem

Let $W(s_E)$ and $U(s_U)$ be the present discounted value of lifetime utility of an employed and unemployed worker in state $s$ before (i) their consumption decision, (ii) the realization of any uncertainty in terms of job loss or the labor market. These two values may be written recursively as follows

1. **Value of employment**

   $$W(s_E) = \max_{c \geq 0} \log(c + \xi) - v(\psi) + \beta \left[ \delta U(a', d', t') \ldots ight.$$  
   
   $$+ (1 - \delta) \int_{\xi}^{\kappa} \max \left\{ -\kappa + \lambda_E \int \max \left\{ W(a', d', t', w, \psi), W(a', d', t', w', \psi') \right\} dF(w', \psi') \right\} dH(\kappa) \right]$$

   s.t.

   $$(d', t', a') = \begin{cases} 
   \left( (1 + r^d) d - \rho(s_E), t - 1, (1 + r^a(a)) a + w - \rho(s_E) - \xi \right) & \text{if } (1 + r(a)) a + w - \Gamma_E(s_E) \geq \rho(s_E) + \xi \\
   \left( \Delta(s_E), \tau(s_E), \Gamma_E(s_E) \right) & \text{if } (1 + r(a)) a + w - \Gamma_E(s_E) < \rho(s_E) + \xi 
   \end{cases}$$

2. **Value of unemployment**

   $$U(s_U) = \max_{c \geq 0} \log(c + \xi) + \beta \left[ (1 - \lambda_U) U(a', d', t') + \lambda_U \int \max \left\{ W(a', d', t', w, \psi'), U(a', d', t') \right\} dF(w', \psi') \right]$$

   s.t.

   $$(d', t', a') = \begin{cases} 
   \left( (1 + r^d) d - \rho(s_U), t - 1 (1 + r^a(a)) a + b - \rho(s_U) - \xi \right) & \text{if } (1 + r(a)) a + b - \Gamma_U(s_U) \geq \rho(s_U) + \xi \\
   \left( \Delta(s_U), \tau(s_U), \Gamma_U(s_U) \right) & \text{if } (1 + r(a)) a + b - \Gamma_U(s_U) < \rho(s_U) + \xi 
   \end{cases}$$
7.3 Baseline repayment policy

Recall that the repayment policy $\mathcal{R} = (\rho, \Delta, \tau)$ captures all of the institutional features associated with student debt. In the baseline model we consider $\mathcal{R}_S$ for Federal Stafford loans under the Standard Repayment Plan.\textsuperscript{17,18} Under this the functions of the repayment policy are as follows

$$\rho_S(s) = \begin{cases} \left[ \left( \frac{r_d}{1 + (1 + r_d) - (r + 1 + r)} \right) \right] d, & \text{if } t > T_G \\ 0 & \text{if } t \leq T_G \end{cases}$$

$$\Delta_S(s) = (1 + r_d) d - \max \left\{ \left( (1 + r(a)) a + w - \Gamma(s) - \varphi_0 \right) + \phi_S \left[ \rho_S(s) - \max \left\{ (1 + r(a)) a + w - \Gamma(s) - \varphi_0 \right\} \right] \right\}$$

$$\tau_S(s) = \begin{cases} T_G + 1, & \text{if } d > 0 \text{ and } t = T \\ t + 1, & \text{otherwise} \end{cases}$$

These rules imply that the repayment $\rho_S$ is calculated to amortize the loan over $T$ periods. If available resources do not cover the full required repayment (i.e. $1 + r(a) a + w - \Gamma(s) \in (0, \rho_S(s))$) then available resources are seized and submitted in partial repayment. We call this delinquency. Under delinquency $\Delta_S$ implies that the loan accrues interest and a penalty of a fraction $\phi_S$ of the (post-seizure) missed payment, minus the partial repayment. The penalty $\phi_S$ is set to 18.5 percent to approximate the effect of default.\textsuperscript{19}

Since any payment which can be made up to the borrowing constraint is enforced, all delinquent borrowers end the period with assets $a' = \Gamma(s)$ and consume $c = \varphi$.\textsuperscript{20} Graduates are initialized with $t = 1$. Payments are deferred for a six month grace period ($T_G = 6$) and the loan is amortized over 10 years ($T = 120$). We do not model renegotiation of the loan explicitly, and so as a stand-in $\tau_S$ implies that we reset the date of the loan to $t = T_G$ in the case that the individual gets to the end of the loan without it being fully amortized.

\textsuperscript{17}Conditional on positive debt, 67% of our sample receive only Federal funding and 30% receive a combination of Federal and private loans (BB08 loansrc). One hundred percent of Federal borrowers hold Stafford loans and 78% hold Stafford loans as their only form of Federal support (BB08 fedlnpak). The remainder receive a combination of Stafford and other Federal support (e.g. PLUS, Pell grants). 99% of Stafford borrowers held both subsidized and unsubsidized loans and of these 48% borrowed less than the total maximum for the program (BB08 staffclt). Recall, that the only difference between sub-/unsup-sidized Stafford loans is the deferment of interest while studying college under the latter. Since $t = 0$ coincides with graduation we do not need to model the difference between these loans.

\textsuperscript{18}For information regarding the Standard Repayment Plan see: https://studentaid.ed.gov/sa/repay-loans/understand/plans/standard. Up until 2010 this was the only payment plan available to borrowers.

\textsuperscript{19}Stafford loans are considered to be in default if they have remained delinquent for 270 days. A loan is delinquent if it is not completely up to date in its repayments. A defaulting borrower does not default in the traditional sense since student debt is essentially non-defaultable. Instead the loan is handed to a collection agency with a fee of 18.5% of the remaining principle. Since modeling this entirely would require additional state-variables we view the above as a reasonable approximation. As another point of reference, a major loan provider Sallie Mae issues a late fee of 6% of the repayment after a payment is 15 days past its due date. Compounded over two periods to get to a month, this is 12.4% (see: http://lifehacker.com/how-one-late-student-loan-payment-affects-you-1326216867).

\textsuperscript{20}In some cases the worker will not be able to finance $c$ even when making no repayments, for example in the case that a worker has negative assets, is unemployed and $ra + b < c$. Since unemployed the worker cannot extend borrowing and their income level (benefits $b$) are insufficient to cover interest payments and the subsitent level of consumption. In reality this is when an individual would default on their debt. Since we do not model default we simply assume that the individual remains at the borrowing constraint and that $c$ is a subsidy from government to the household.
8 Estimation

The unknown parameters and functional forms of the model are the repayment policy \( R = (\rho, \Delta, \tau) \) and

\[
\begin{align*}
\theta_1 &= \{ \beta, \delta, r^d, r^a(a), \gamma, b \} \\
\theta_2 &= \{ v(\psi), F(w, \psi), H(\kappa), \lambda_U, \lambda_E \}
\end{align*}
\]

We will externally calibrate \( \theta_1 \) and then make the following relatively simple observation: for a student graduating with \( d = 0 \) all of the parameters in \( \theta_2 \) enter their problem while \( R \) does not. Our strategy is to estimate \( \theta_2 \) on the sub-sample of the BB08 data without student debt. The repayment policy \( R \) is entirely determined by institutional rules and parameters. With \( \theta_2 \) estimated and \( R \) specified we can then test the model’s fit with respect to labor market and loan delinquency outcomes for indebted students. We consider this a particularly neat exercise in out-of-sample testing. The model is solved at a monthly frequency and estimated on 2008/09 data. All rates are expressed at a yearly frequency.

8.1 Calibration - \( \theta_1 \)

We assume a rate of time preference \( \beta \) equal to 0.95\(^{1/12} \). Following Kaplan and Violante (2014) (henceforth KV) we specify an annual real return on positive assets \( r^{a_+} = -2\% \) given the nominal return of zero after 2008 and two percent inflation. The average nominal rate on consumer credit cards given by the Federal Reserve’s Consumer Credit report was 14\% in 2009 which is the same as the average rate paid by college graduates in the Survey of Consumer Finance 2001 (SCF01), so we set \( r^{a_-} = 12\% \).\(^{21} \) The interest rate on student debt is modeled after Stafford loans which are nominal, fixed rate loans. In academic years 2006-07 and 2007-08 the rate was 6.80\%, so we set \( r^d = 4.8\% \).\(^{22} \)

Given the lack of information regarding credit limits in the BB08 we use SCF01 to calibrate \( \gamma \). The survey asks households to report their total credit limit. Using the same sample as KV we find a median ratio of credit limits to annual labor income for college-graduates aged 25 to 30 of 21\%. This is higher than found in KV (18.5\%) due to excluding those without a college degree, which have a median limit of only 15\% (see Figure 8).\(^{23} \)

The rate of separation from employment \( \delta \) we take from Shimer (2005) as 0.034 at a monthly frequency. The separation rate could well be higher for younger workers but for now we simply use the estimate across all workers.\(^{24} \)

The Federal poverty threshold for an individual living alone in 2008 was $991/month. In our estimation sample of 1,439 workers only 20 have a monthly income less than this amount. We therefore set \( c \) to $991.\(^{25} \)

We assume that the worker gains access to unemployment benefits \( b \) which are sufficient to cover a half of \( c \). Computing average benefits for unemployed workers in the SCF01 gives approximately this result.

\(^{21}\)See: http://www.federalreserve.gov/releases/g19/ : G19

\(^{22}\)Prior to 2006-07 rates were variable and fluctuated around this figure. From 2013 onwards - due to The Bipartisan Student Loan Certainty Act 2013 – the rate will be equal to the minimum of the 10-year T-Bill rate and 8.25\%. See: https://www.edvisors.com/college-loans/federal/stafford/interest-rates/

\(^{23}\)An interesting fact emerges when decomposing the data this way. When comparing college to non-college workers the within group increase in the credit limit with age is far less significant than the between group difference in average credit limits: the median credit limits for non-college students is 15.5\% and 20.0\% for college graduates. In fact the increase by age is statistically insignificant for college graduates while increasing from a median of 13.1\% among 20-25 year old non-college graduates to 16.1\% for ages 40-45. Hence we feel comfortable making this limit age dependent.

\(^{24}\)Jarosch (2015) estimates a negative correlation between wages and separation rates in the distribution of jobs and that the separation risk falls by around 3\% upon each transition.

\(^{25}\)See: https://www.census.gov/hhes/www/poverty/data/threshld/thresh08.html
8.2 Indirect inference - $\theta_2$

The parameters of $\theta_2 = \{ v(\psi), F(w, \psi), H(\kappa), \lambda_U, \lambda_E \}$ are jointly estimated by indirect inference given the functional forms that we now specify. We assume that $v(\psi) = 1/\psi$ which satisfies the assumptions made in the model of Section 6. Search costs are assumed to be distributed uniformly with mean $\kappa$ and upper bound $\bar{\kappa}$.

In order to map the model to the data we assume that job satisfaction may be low or high, $\psi \in \{ \psi_L, \psi_H \}$. This allows us to fully characterize the joint distribution $F(w, \psi)$ using two conditional densities $F_L(w)$ and $F_H(w)$ and a probability $p_H$ of drawing a high satisfaction job. We assume that these conditional densities are log-normal

$$
\psi = \begin{cases} 
\psi_L & \text{w.p. } (1 - p_H) \\
\psi_H & \text{w.p. } p_H
\end{cases}
$$

$$
\log w|\psi_k \sim N(\tilde{\mu}_k, \tilde{\sigma}_k^2)
$$

The population distribution $F(w, \psi)$ from which agents draw offers is distinct from what we call the sample distribution $\tilde{F}(w, \psi)$ which is the distribution of workers over $(w, \psi)$ one year after graduating college. We impose the same parametric form on the data to give estimates of $\tilde{p}_H$ and $\{\tilde{\mu}_k, \tilde{\sigma}_k\}_{k \in \{L, H\}}$ which we treat as moments in the estimation.

To form estimates of $\tilde{\mu}_H$, $\{\tilde{\mu}_k, \tilde{\sigma}_k\}_{k \in \{L, H\}}$ we assign workers in our sample to low and high satisfaction groups. We first constructing a measure $s_i$ which is equal to the average response to non-pay related job satisfaction questions. $^{26}$ Individuals are then split into high and low satisfaction groups according to the median value of $s_i$, allowing us to fit a log-normal distribution $\log w_k \sim N(\tilde{\mu}_k, \tilde{\sigma}_k)$ to each of the conditional wage distributions. $^{27}$ Figure 9A shows this to be a good approximation.

$^{26}$For each question $j \in J$ we observe answer $a_{i,j} \in \{0, 1\}$ and compute $s_i = \sum_{j \in J} a_{i,j}$. The set of questions $J$ relate to job importance, security, career industry, overall satisfaction and relevance to major. For the precise text of the questions see Appendix B.

$^{27}$It turns out that $s_i = 1$ for more than half the sample. We therefore model these as having $\psi_H$ and all others as $\psi_L$ giving
Figure 9: Wage and asset distributions

### Notes
1. Panel (A) plots kernel smoothed densities of monthly wages (in thousands of dollars) in solid and the log-normal fit of these distributions in dashed lines. (ii) Panel (B) plots a kernel smoothed density of summer savings from the year before college (BB08 jobsave) (in thousands of dollars) together with an exponential and log-normal fit. (iii) For both panels the data are from BB08 corresponding to our estimation sample for workers without student debt.

Given these simplifications we have eleven unknown parameters \( \theta_2 = \{ \kappa, \bar{\kappa}, \lambda_U, \lambda_E, \psi_L, \psi_H, p_H, \mu_L, \mu_H, \sigma_L, \sigma_H \} \) to estimate by indirect inference.

### Data

The estimation sample consists of \( n = 940 \) students that satisfy the following conditions: (i) unemployed upon graduation, (ii) without student debt. The data is \( X_{n}^{\text{Data}} = \{ E_i, j_i, w_i, d_i, \psi_i, S_i \}_{i=1}^{n} \) which consists of observations on employment status \( E_i \), number of jobs since graduation \( j_i \), monthly wage \( w_i \), duration of search after graduation \( d_i \), our constructed measure of job satisfaction \( \psi_i \), and an indicator of active job search \( S_i \in \{0, 1\} \).

### Simulation

Given a vector of parameters \( \psi \) we compute moments from the model as follows. Policies are solved under \( \psi \) and then used to simulate \( s = 1, \ldots, S \) samples of size \( n \) for 12 months to derive a dataset \( X_{n}^{\text{Model}} \). Moments are computed for each of the \( s \) samples and we average moments across samples to compute an expectation of the moments. At \( t = 0 \) workers are unemployed and endowed with asset \( a_{i,0} \) which are drawn from \( \log a_{i,0} \sim N(\mu_a, \sigma_a) \) with probability \( p_a \) and set to zero with probability \( (1 - p_a) \). BB08 does not provide data on savings, though does contain data on savings due to work over the previous summer. We use this to estimate \( p_a = 0.35, \mu_a = 0.376 \) and \( \sigma_a^2 = 0.817 \) (see Figure 9B).\(^{28}\)

### Moments

The 12 moments used in our estimation of the 11 parameters are as follows, where \( n_E = \sum_{i=1}^{n} I[E_i = 1] \)

\[ \hat{p}_H = 0.374. \]

\(^{28}\)In future versions of the estimation of the model we may proceed in two ways. We could assume that \( \log a_{i,0} \sim N(\mu_a, \sigma_a) \) and estimate these parameters along with \( p_a \), adding three parameters to the joint estimation. Alternatively we could assume that \( a_{i,0} = \omega \times \tilde{a}_{i,0} \) where \( \tilde{a}_{i,0} \) is summer savings as distributed in the data and estimate only \( \omega \), i.e. assume that initial wealth is perfectly correlated with summer savings.
1. Maximum likelihood estimates of the parameter $\nu$ of a simple hazard model of unemployment $p(u) = \nu e^{-\nu t}$ so that $\hat{\nu} = \bar{D}_n = \frac{1}{n} \sum_{i=1}^{n} 1_{[E_i = 1]} d_i$

2. Average number of jobs since graduation $\bar{J}_n$, fraction of employed workers searching $\bar{S}_n$, and fraction of workers unemployed $\bar{U}_n$

$$\bar{J}_n = \frac{1}{n} \sum_{i=1}^{n} 1_{[E_i = 1]} j_i, \quad \bar{S}_n = \frac{1}{n} \sum_{i=1}^{n} 1_{[E_i = 1]} s_i, \quad \bar{U}_n = \frac{1}{n} \sum_{i=1}^{n} 1_{[E_i = 0]}$$

3. The coefficients of a linear probability model estimated on employed workers

$$S_i = \beta_0 + \beta_w \frac{w_i}{1000} + \beta_\psi 1_{[\psi_i = \psi_H]} + \varepsilon_i$$

4. Maximum likelihood estimates of the parameters of the sample distribution of $(w_i, \psi_i)$ under the same parametric specification as the population distribution

$$\hat{\mu}_k = \frac{1}{n_{E,k}} \sum_{i=1}^{n} 1_{[E_i = 1, \psi_i = \psi_k]} \log w_i, \quad k \in \{L, H\}$$

$$\hat{\sigma}^2_k = \frac{1}{n_{E,k}} \sum_{i=1}^{n} 1_{[E_i = 1, \psi_i = \psi_k]} \left( \log w_i - \hat{\mu}_k \right)^2, \quad k \in \{L, H\}$$

$$\hat{p}_H = \frac{1}{n} \sum_{i=1}^{n} 1_{[E_i = 1, \psi_i = \psi_H]}$$

**Estimation**

Estimation of the parameters is achieved using a minimum distance estimator (MDE) based on the set of 12 moments $\hat{m}_n$ described above. This could be described as SMM or Indirect Inference. We define the following criterion function

$$\mathcal{L}_n(\theta) = -\frac{n}{2} (\hat{m}_n - m(\theta))^T W_n (\hat{m}_n - m(\theta))$$

and the associated MDE $\hat{\theta}^{MDE}_n = \arg \max_{\theta \in \Theta} \mathcal{L}_n(\theta)$. The weighting matrix $W_n$ is constructed from a consistent estimate of the asymptotic variance covariance matrix of the moments $\Sigma$ which satisfies $\sqrt{n} (\hat{m}_n - m(\theta_0)) \xrightarrow{d} \mathcal{N}(0, \Sigma)$. This is found by boot-strapping from the data to obtain $\hat{\Sigma}_n$ and then taking $W_n = \left( \text{diag} \left[ \hat{\Sigma}_n \right] \right)^{-1}$.\(^{29}\)

Since the objective function possibly has many local maxima and is prone to simulation error we implement the Laplace Type pseudo-likelihood estimator presented in Chernozhukov and Hong (2003).\(^{30}\) This has the added advantage of being able to compute standard errors directly from the quasi-posterior. Given a prior $\pi(\psi)$ the quasi-posterior $p_n(\psi)$ is a proper distribution density

$$p_n(\theta) = \frac{\exp \left( \mathcal{L}_n(\theta) \right) \pi(\theta)}{\int_\psi \exp \left( \mathcal{L}_n(\theta) \right) \pi(\theta) d\psi}.$$

To construct $p_n(\theta)$ we proceed by Markov-chain Monte-Carlo (MCMC) methods. Given an initial $\theta^1$ we

\(^{29}\)In taking the diagonal we ignore the correlations between moments which may be imprecisely measured in small samples given that some are fourth order.

\(^{30}\)For recent applications in labor and macroeconomics see Lamadon (2014), Jarosch (2015) and Lise (2013).
draw a proposal $\theta^* \sim q(\psi|\psi^j)$ which we then accept with probability
\[
d(\theta^j, \theta^*) = \min \left( \frac{\exp \left( \mathcal{L}_n(\theta^*) \right) \pi(\theta^*) q(\theta^j|\theta^*)}{\exp \left( \mathcal{L}_n(\theta^j) \right) \pi(\theta^j) q(\theta^*|\theta^j)} , 1 \right).
\]

This procedure is repeated many times to obtain a chain of length $B$ that represents the quasi-posterior distribution $p_n(\theta)$. Choosing the prior $\pi(\theta)$ to be uniform over $\Theta = \times_{j=1}^J [\bar{\theta}_j, \bar{\theta}_j]$, and a symmetric proposal density $\theta^* \sim \mathcal{N}(\theta^j, \xi)$ results in the simple rule
\[
d(\theta^j, \theta^*) = \min \left( \exp \left( \mathcal{L}_n(\theta^*) - \mathcal{L}_n(\theta^j) \right) , 1 \right).
\]

In practice we parallelize the estimation algorithm. We simulate $C = 20$ chains in parallel each of length $B = 10,000$ and use the last $B^* = 2,000$ elements (pooled over the $C$ chains) to obtain parameter estimates. The point estimate is then
\[
\hat{\theta}_n = \frac{1}{C \times B^*} \sum_{c=1}^C \sum_{b=1}^{B-B^*} \theta^b_c.
\]

The quasi-posterior $p_n(\theta)$ as approximated by the Markov Chain can be used directly to construct confidence intervals for the parameter estimates. Note that given the criterion function $\mathcal{L}_n(\theta)$ with moments $\hat{m}_n$, true parameter $\theta_0$ and consistent weighting matrix $W_n$, the asymptotic variance of the minimum distance estimator $\hat{\theta}_n$ is described by the following limit
\[
\sqrt{n} \left( \hat{\theta}_n - \theta_0 \right) \overset{d}{\rightarrow} \mathcal{N}(\theta_0, J^{-1} \Omega J^{-1})
\]
where
\[
\Omega = \lim_{n \rightarrow \infty} \left[ \frac{\partial m(\theta_0)}{\partial \theta'} \right] W_n \Sigma W_n \left[ \frac{\partial m(\theta_0)}{\partial \theta'} \right]^T,
\]
\[
J = \lim_{n \rightarrow \infty} \frac{1}{n} \frac{\partial^2 \mathcal{L}_n(\theta)}{\partial \theta^i \partial \theta^j}.
\]

We construct a consistent estimate of $\partial m(\theta_0)/\partial \theta'$ by finite-differences around $\hat{\theta}_n$, a consistent estimate of $\Sigma$ by boot-strapping from a simulation sample at $\hat{\theta}_n$, and a consistent estimate of $J$ from the variance-covariance matrix of the parameters generated by the Markov chain.

### 9 Model fit

Parameter estimates are given in Table 2 and the values of target moments in Table 3. The overall fit of the model is good, with the moments closely matching those found in the data. Column (3) shows the standard deviation of the moments from the data, construct by boot-strapping samples with replacement from our data. Column (4) provides similar statistics from the model. We find it reassuring that even given the limited degree of ex-ante heterogeneity, the model generates similar sized uncertainty surrounding these

---

31 The covariance matrix of the proposal density $\Xi$ is initialized as a diagonal matrix with diagonal entries equal to $\psi^0$. The scaling parameter $\xi$ is then moved to maintain an acceptance rate around 0.3. After a burn-in of length 2,000 I replace $\Xi$ with the variance-covariance matrix of the series for $\psi$ pooled across all chains and re-set $\xi$ to one. I then continue to adjust $\xi$ to achieve the desired acceptance rate.

32 Current estimates of the standard errors of parameters are forthcoming.
moments suggesting that the statistical properties of the data generated by the model are close to the data not only in terms of means of moments.\footnote{To see this point consider a case in which the model was generating identical sample paths for each worker, then the values in column (4) would all be zero.}

The model is unable to generate the high fraction of workers searching on the job. Parameterizations of the model in which we are able to match \( S_n \) are notable for generating excess unemployment and high durations of unemployment straight out of college. In order to encourage search, unemployment must be sufficiently unappealing and the model cannot achieve this without excessive unemployment durations. We are currently working on modifications to the model that allow us to replicate these features of the data. The results presented in this version of the paper correspond to the parameters in the tables below.

### Table 2: Parameter estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Mean utility cost of search ( \kappa )</td>
<td>1.771</td>
<td>-</td>
</tr>
<tr>
<td>2. Ratio of ( \bar{\kappa} ) to ( \kappa )</td>
<td>1.842</td>
<td>-</td>
</tr>
<tr>
<td>3. Unemployed job-arrival probability ( \lambda_{U} )</td>
<td>0.949</td>
<td>-</td>
</tr>
<tr>
<td>4. Employed job-arrival probability ( \lambda_{E} )</td>
<td>0.226</td>
<td>-</td>
</tr>
<tr>
<td>5. Low job-satisfaction parameter ( \psi_{L} )</td>
<td>1.736</td>
<td>-</td>
</tr>
<tr>
<td>6. High job-satisfaction parameter ( \psi_{H} )</td>
<td>1.130</td>
<td>-</td>
</tr>
<tr>
<td>7. Sampling: Mean of log ( w ) for ( \psi_{L} ) ( \mu_{L} )</td>
<td>0.912</td>
<td>-</td>
</tr>
<tr>
<td>8. Sampling: Mean of log ( w ) for ( \psi_{H} ) ( \mu_{H} )</td>
<td>1.086</td>
<td>-</td>
</tr>
<tr>
<td>9. Sampling: Variance of log ( w ) for ( \psi_{L} ) ( \sigma^2_{L} )</td>
<td>0.122</td>
<td>-</td>
</tr>
<tr>
<td>10. Sampling: Variance of log ( w ) for ( \psi_{H} ) ( \sigma^2_{H} )</td>
<td>0.131</td>
<td>-</td>
</tr>
<tr>
<td>11. Sampling: Probability of ( \theta_{H} ) ( p_{H} )</td>
<td>0.550</td>
<td>-</td>
</tr>
</tbody>
</table>

**Notes**

(i) Column (1) gives the values of \( \hat{\theta}_{MCMC} \).

(ii) Column (3) gives the square roots of the diagonal elements of the variance-covariance matrix of the pooled chains used to construct \( \hat{\theta}_{MCMC} \) (forthcoming).
Table 3: Target moments

<table>
<thead>
<tr>
<th>Moment</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Data (1)</td>
<td>Model (2)</td>
</tr>
<tr>
<td>A. Sample means</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Duration ¯ D̄ₙ</td>
<td>2.501</td>
<td>2.590</td>
</tr>
<tr>
<td>Number of jobs ¯ Jₙ</td>
<td>1.524</td>
<td>1.425</td>
</tr>
<tr>
<td>Search indicator ¯ Sₙ</td>
<td>0.186</td>
<td>0.104</td>
</tr>
<tr>
<td>Unemployment indicator ¯ Uₙ</td>
<td>0.079</td>
<td>0.101</td>
</tr>
<tr>
<td>B. Regression coefficients</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept ˆ β₀</td>
<td>0.490</td>
<td>0.523</td>
</tr>
<tr>
<td>Wage ($000) coefficient ˆ βₚ</td>
<td>-0.031</td>
<td>-0.070</td>
</tr>
<tr>
<td>High satisfaction coefficient ˆ βₚ</td>
<td>-0.282</td>
<td>-0.236</td>
</tr>
<tr>
<td>C. Observed distribution parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean of log w for ( \psi_L ) ( \hat{\mu}_L )</td>
<td>1.098</td>
<td>1.201</td>
</tr>
<tr>
<td>Mean of log w for ( \psi_H ) ( \hat{\mu}_H )</td>
<td>1.148</td>
<td>1.215</td>
</tr>
<tr>
<td>Variance of log w for ( \psi_L ) ( \hat{\sigma}^2_L )</td>
<td>0.175</td>
<td>0.110</td>
</tr>
<tr>
<td>Variance of log w for ( \psi_H ) ( \hat{\sigma}^2_H )</td>
<td>0.143</td>
<td>0.093</td>
</tr>
<tr>
<td>Probability of ( \psi_H ) ( \hat{p}_H )</td>
<td>0.716</td>
<td>0.724</td>
</tr>
</tbody>
</table>

Notes (i) Column (1) gives the mean of moments from a bootstrap of the data with 10,000 re-samples (these are associated with the diagonal of the weighting matrix \( W_n \) used in estimation). (ii) Column (2) gives the mean of the moments from the \( S = 1,000 \) simulations of the model used to compute \( L_n(\theta) \). (iii) Column (3) gives the standard deviation of the moments from the same bootstrap exercise used for column (1). (iv) Column (4) gives the bootstrap standard standard deviations of the moments from 10,000 re-samples of one simulated sample.

Comparing low and high asset workers

In Figure 10 we show the evolution of cohort means of observable variables in the model for the two year period following leaving college and entering the labor market. We compare the paths for a cohort with zero assets and one with high assets where we draw \( a_{i,0} \) from the upper quartile of the initial distribution of assets \( \log a_{i,0} \sim N(\mu_a, \sigma_a^2) \). The model reinforces the theoretical results from the previous section. Workers in a higher initial asset position when unemployed are more selective in the labor market, rejecting more offers leading to higher initial wages and job satisfaction when employed. The correlation that the model generates between assets and unemployment is therefore positive. Since low asset workers accept more offers when unemployed they also incur costs and search more when employed and continue to accept more offers when employed than high asset workers. In terms of the trade-off between wages and job satisfaction, for now we note that the profile of wages is more similar across groups than for satisfaction as low asset workers focus their search on higher wages and high asset workers focus on job satisfaction. We return to this point more carefully in Section 12 when we turn to quantifying this trade-off.

Comparing sampling and population distributions

In Figure 11 we plot the population wage distribution (from which agents draw offers) and the resulting sampling distribution which is the counterpart to that which we measure in the data one year after graduation. Note from Tables 2 and 3 that we match the properties of the sample distribution well. From the sampling distribution this requires an underlying positive correlation between wages and job satisfaction: \( \mu_L < \mu_H \). We
Figure 10: Comparison of low and high debt cohorts

Notes (i) Simulated cohorts have 100,000 workers, (ii) All workers in low asset cohort are initialized with $a_{i,0} = 0$, (iii) All workers in the high asset cohort draw $a_{i,0}$ from the upper quartile of the initial distribution of assets $\log a_{i,0} \sim N(\mu_a, \sigma_a^2)$

view this as an innate technological feature of the jobs that workers can draw from since the job satisfaction data that we use pertains to non-wage aspects of work. In terms of the variances, the variance of wages in high satisfaction jobs is lower than that for low satisfaction jobs. This creates a tension in the model since if workers first take low satisfaction positions then the lower variance of high satisfaction wages discourages search on the wage dimension.

Identification

To be added Discussion of identification of (i) $\psi_L$ versus $\psi_H$, and (ii) $\lambda_U$ versus $\lambda_E$.

10 Results - Role of student debt

In this section we consider the predictions of the model with student debt for the behavior detailed in Section 4, specifically the influence of student debt on the wage-satisfaction trade-off and search. Since we did not target moments related to student debt in our estimation of the model we view these as positive results for the model.

1. Trade-offs

We first consider how well the model replicates the observed behavior in Figures 5 and 4. In Figure 12 we plot the model fraction of workers with (A) high job satisfaction and (B) searching conditional on income and debt to income quantiles. We find that the model is broadly consistent with the data. Conditional
on income, as the debt/income level of a worker increases we find a lower likelihood that the worker is in a high satisfaction job and increased likelihood of search. Workers with high debt-income ratios have a high incentive to both trade-off job satisfaction for higher wages and to find higher wage jobs to fund their required repayments so as to avoid penalty. Recall that we have built into the model a positive correlation between wages and job satisfaction which explains some but not all of the correlation in panel A. As in the data, the effects on satisfaction and search are most profound at lower income levels.

2. Evolution of cohorts

We next consider the evolution of cohorts means of the same variables as Figure 10 for no debt, medium debt ($d_{i,0} = \$40,000$) and high debt ($d_{i,0} = \$85,000$) cohorts of workers. In all cases we set initial assets to zero. The behavior is broadly consistent with our expectations. In the first period all workers are unemployed. Those with higher debts desire higher wage jobs to meet the repayments on their debts which will become due after 6 months. Given that on-the-job search is costly, high debt graduates use the grace period to accept fewer initial wage offers than medium debt graduates who in turn accept slightly fewer than those with no debts. This job selection leads to high debt graduates having initial jobs with higher wages. Since wages are correlated with job satisfaction in the population distribution they also have higher job satisfaction. When on-the-job high debt graduates both search more and are more selective, seeking higher wage jobs and prepared to trade off job satisfaction. This is found in their lower acceptance rate and the fact that although their wages remain higher, their job satisfaction falls relative to lower or no debt graduates. All of these patterns are maintained when comparing the medium and no debt graduates.

Finally, we note the effect that the timing of the first repayment has on job acceptance for high debt students. Seven months after graduating first repayments on student loans become due and the acceptance rate for unemployed high debt graduates jumps up, diverging from medium and no debt and causing satisfaction to further diverge from other students and a kink in the profile of high debt cohort wages as more low wage jobs are accepted to meet their repayments. Overall we find strong qualitative support of the effect
of student debt on search, wages and job satisfaction and this appears to be of at least mild quantitative importance.

11 Results - Evaluating repayment policies

In this section we use the estimated model to evaluate the effect of different repayment policies on worker behavior, total student welfare and net repayments. Given the estimation of our model we emphasize that the results in this section should be interpreted as follows. Consider computing the model under policies $R$ and $R'$ and computing a moment $m$ and $m'$ from a simulated cohort of graduates under each policy. Then $m' - m$ is the model’s prediction of the counterfactual change in that moment under the assumption that $R'$ is an unanticipated policy change enacted upon the student’s date of graduation. In Appendix C we detail an extension of the model to accommodate an endogenous choice of college and debt and suggest how this could be estimated. Under such an extension we could consider the arguably more interesting policy question of how changes to $R$ effect the composition of borrowers.

**Definition.** Total welfare under repayment policy $R$ and parameters $\theta$ is

$$W(R, \theta) = \frac{1}{S} \sum_{s=1}^{S} U_s(R, \theta), \quad U_s(R, \theta) = \frac{1}{n} \sum_{i=1}^{n} U(a_{(i,s),0}, d_{(i,s),0} | R, \theta).$$

Consumption welfare $W_c(R, \psi)$ and non-pecuniary welfare $W_\psi(R, \psi)$ are computed similarly but only count the utility flows from consumption and job satisfaction respectively.

**Income based repayment plan**

Our main policy experiment considers the effect of a change from the standard repayment plan $R_S$ under which we have so far proceeded to an **Income Driven Repayment Plan (IDR) $R_I$**. IDR plans were introduced, unexpectedly, in 2010. Therefore a sudden change to $R_I$ seems like a valid experiment. The repayment policy $R_I = (\rho_I, \Delta_I, \tau_I)$ is as follows - noting that the condition for delinquency is the same - $$(1 + r(a))a + w - \Gamma(s) < 0.$$
Figure 13: Comparison of zero, low and high debt cohorts

Notes: (i) Simulated cohorts have 100,000 workers each, (ii) All workers are initialized with $a_{i,0} = 0$, (iii) High debt workers are initialized with $d_{i,0} = 85,000$, medium debt workers are initialized with $d_{i,0} = 40,000$.

\[ \rho_I(s) + c. \]
\[
\rho_I(s) = \max\{0.15 \times (w - 1.5c), 0\}
\]
\[
\Delta_I(s) = \Delta_S(s)
\]
\[
\tau_I(s) = \tau_S(s)
\]

Under $R_I$ repayments are 15 percent of disposable income, where disposable income is defined as wages minus 150 percent of the Federal poverty level $c$ which in 2008 was $933/month.\(^{34}\) If wages are less than 150 percent of the Federal poverty level then repayments are zero.\(^{35}\) Under the implemented policy three further features were added that we do not consider in our analysis: (i) debt would be forgiven after 25 years, (ii) in the case that repayments $\rho_I(s)$ are less than interest accrued $r^d d_s$, the government would pay the remaining interest to avoid negative amortization, (iii) the actual required repayment would be the minimum of $\rho_I(s)$ as defined here and the payment required under a Standard Repayment policy $\rho_S(s)$. For now we ignore these changes and assess welfare under only the changes to $\rho$. This is a cleaner experiment and is comparable to the implementation of income based repayment schemes in other countries such as Australia and the United Kingdom. We will later consider adding these additional features, especially in order to compute the implied cost to the government for running a repayment system that subsidizes default and delinquency.

\(^{34}\)See: https://www.census.gov/hhes/www/poverty/data/threshld/thresh08.html

\(^{35}\)All plans are computed annually and then effective for the following year however if large income fluctuations occur within a year then individuals can have their repayment re-assessed. Therefore the monthly determination model seems fine (see: StudentAid.gov).
Table 4: Decomposing welfare across repayment plans

<table>
<thead>
<tr>
<th></th>
<th>Standard ( R_S )</th>
<th>Income based ( R_I )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total welfare</td>
<td>( \mathbb{E}<em>0 \sum \beta^t [u(c</em>{i,t}) - \psi_{i,t} - 1_{S_i,t}\kappa_{i,t}] )</td>
<td>-</td>
</tr>
<tr>
<td>Consumption</td>
<td>( \mathbb{E}<em>0 \sum \beta^t u(c</em>{i,t}) )</td>
<td>-</td>
</tr>
<tr>
<td>Search costs</td>
<td>( \mathbb{E}<em>0 \sum \beta^t [-1</em>{S_i,t}\kappa_{i,t}] )</td>
<td>-</td>
</tr>
<tr>
<td>Work disutility</td>
<td>( \mathbb{E}<em>0 \sum \beta^t [-\psi</em>{i,t}] )</td>
<td>-</td>
</tr>
</tbody>
</table>

Results

We solve the model under \( R_I \) at the estimated set of parameters. In Figure 14 we plot welfare for employed and unemployed workers under each of the repayment plans for the first year following graduation. We find that at low debt levels individuals prefer the standard repayment policy, while at high debt levels the income based repayment program is preferred. At low debt levels repayments are small under the standard repayment policy while they can be quite large under the income based repayment program. At high debt levels the standard repayment policy requires large repayments that cripple the borrower. The borrower with $40,000 worth of debt has an initial repayment of $500/month at the end of the grace period, while under \( IBR \) this is only $200. This has the consequence of delivering higher consumption to the worker early on in their career when consumption is low, and hence is highly valued at high levels of debt. For these reasons welfare under the \( IBR \) is flat in debt since the repayments are determined only by the wage, the slight downward slope is due to the longer horizon until repayment for those more highly indebted.

We can compute the average welfare under both plans by integrating initial values across the observed distribution of initial assets \( a_{i,0} \) and debt \( d_{i,0} \). We use log-normal approximations to the unconditional distributions of each variable as the marginal density and treat the two as independent, computing welfare as

\[
W(R) = \int \int W(a_i, d_i, 1)F_a(a_i)F_d(d_i)da_i dd_i.
\]

We find that \( W(R_S) = 1.582 \) and \( W(R_I) = 1.591 \), which are remarkably similar. The reason for these being so close is two-fold. First, the profiles of welfare over debt are largely independent of initial assets \( a_{i,0} \). Second, the distribution of debt has a mean of $19,433, which considering Figure 14 implies that those that prefer \( R_S \) offset those that prefer \( R_I \). In fact the fraction of individuals preferring \( R_S \) is 36.2 percent. We caution that in this version of the paper we have not included the costs associated with default and are merely assessing the student-welfare rather than that of the loan-system as a whole. We plan to add further to these computations.

In a future version of this paper we will decompose the welfare under both sets of plans according to Table 4, which can be easily computed by simulation.

12 Results - Evaluating job satisfaction

An interesting quantitative application of the model is to measure the value of job satisfaction. Given the solution of the model under the baseline set of parameters we can ask how much the worker values a transition from a low to a high satisfaction job in terms of (i) trade-off of wages, (ii) life-time consumption and (iii) how search behavior changes over satisfaction levels. To conduct this analysis we abstract from student debt, setting \( d = 0 \) for all workers.
Notes The figure plots the values taken on by the value function for unemployment $U(a,d,t)$ under the range of values for $d$ given on the x-axis, and values of $a = 0$ and $t = 1$. These are plotted for the model solved under the baseline set of parameters under $R_I$ and $R_S$.

Consumption compensation

First we determine the certain reduction in consumption in all states that an individual with $s = (a,w,\psi_L)$ would be willing to suffer in order to transition to a high satisfaction job, keeping the same wage $w$. That is, we compute the function $\Omega(a,w)$ that satisfies

$$W^{\Omega}(a,w,\psi_H) = \mathbb{E}_0 \sum_{s=0}^{\infty} \beta^s \left[ u((1-\Omega(a,w))c_s) - 1/\psi_s \mid \psi_0 = \psi_H, w_0 = w \right] = W(a,w,\psi_L)$$

We repeat the exercise for three cases: (i) under the baseline parameters, (ii) under $\bar{\kappa} = 0$, i.e. free search, (iii) setting the conditional wage distribution for low satisfaction draws equal to high satisfaction draws, and for two levels of assets $a_L = 0$ and $a_H = 20,000$. We plot results in Figure 15.\footnote{Under log utility we have the simple result that $\Omega(a,w) = 1 - \exp\{(1 - \beta) [W(a,w,\psi_L) - W(a, w, \psi_H)]\}$.}

This exercise demonstrates that a worker in a low satisfaction job at date $t$ would be willing to give in the range of 2 to 6 percent of life-time consumption from date $t$ onwards to transition to a high satisfaction job at the same wage. We first consider the baseline case. For both levels of assets, higher wages in the low satisfaction job imply higher consumption a higher in the marginal rate of substitution between consumption and job satisfaction and a higher willingness to forego consumption. At low wages consumption is higher for the high asset worker leading to $\Omega(a_H, w) > \Omega(a_L, w)$. At higher wages, this relationship is flipped, a point we return to in a moment.

In the case with zero search costs, the value of a free transition from $\psi_L$ to $\psi_H$ - which this experiment measures - is less valuable since the worker can search for free in subsequent periods increasing the value of $W(a, w, \psi_L)$. This leads to a lower value of $\Omega_{[\kappa=0]}(a,w) < \Omega(a,w)$ for all $(a,w)$. This difference is greatest for pairs of $(w, a)$ where the worker is least likely to search at $\psi_L$ under the baseline calibration, for example when wages are already high or wages are low but assets are high.

In the case where we eliminate the correlation between wages and job satisfaction in the offer distribution...
Figure 15: Life-time consumption equivalent value of high job-satisfaction

$F(w, \psi)$ workers value a free transition to $\psi_H$ less. The reason is, again, an increase in $W(a, w, \psi_L)$ due to the more favourable offer distribution. We note that this difference is not large, implying that it is not merely the baseline correlation that is driving the heterogeneous valuations of job satisfaction across assets.

We now explain the crossing of $\Omega(a_L, w)$ and $\Omega(a_H, w)$ for high wages - why a transition is more valuable to low asset workers at high wages. This is due to the value of search in the model. To make this clear we take the baseline calibration under the following restrictions: (i) $\delta = 0$ so jobs are permanent, (ii) $\kappa = 0$ so that on-the-job search is free, (iii) the distribution of $w$ conditional on either $\psi$ is identical and uniform over the range of 1st to 99th percentile wages under $F(w|\psi_H)$, (iv) we set $\lambda_U = \lambda_E = 0.44$, the average job finding rate in the economy. Under these restrictions $\Omega(a_L, w)$ and $\Omega(a_H, w)$ still cross. We then consider a new Baseline with $p_H = 0.5$ to cases with $p_H \in \{0, 1\}$ and compute a simpler measure $\Delta(a, w) = W(a, w, \psi_H) - W(a, w, \psi_L)$ for the same asset levels as above and varying wages. Figure 16 shows that the interior value of $p_H \in (0, 1)$ is the key determinant of this behavior: $\Delta[p_H=0](a_H, w) > \Delta[p_H=1](a_L, w)$ for all wages while the opposite is true for $p_H = 1$. We now provide an understanding for this.

First we explain the behavior in panel A. With the distribution of wages bounded above by $\bar{w}$ then under $p_H = 0$ and $\delta = 0$ at the upper bound $\Delta[p_H=0](a, \bar{w}) = \frac{v(\psi_L) - v(\psi_H)}{1 - \beta}$. That is the difference in life-time utility depends only on job satisfaction and is independent of assets. Indeed this is what we observe in panel A. At low values of wages, the intuition described above is again relevant: there is a meaningful trade-off between wages and job-satisfaction that is induced by a worker’s asset position. If $p_H = 0$, then the value for $W(w, a, \psi_L)$ falls substantially relative to the case of $p_H = 0.5$, and a positive asset worker will give up substantial consumption to transition. Yet if $a = 0$ then as $w \rightarrow 0$ lifetime utility $W(a, w, \psi_L)$ becomes comprised of unbounded negative consumption utility terms and bounded negative disutility of labor terms (since $v(\psi_L)$ is a fixed), hence $\lim_{a \rightarrow 0} \lim_{w \rightarrow 0} W(a, w, \psi_H) - W(a, w, \psi_L) = 0$ under all values of $p_H$, visible in the convergence of the two blue lines.

Now consider the extreme case of $p_H = 1$. High satisfaction jobs are now a certainty upon successful search yet the wage of job draws is still uncertain. Given a wage $w$ suppose for now that all workers of all

---

37Note that $\Delta(a, w)$ is simply a monotonic transformation of $\Omega(a, w)$. 

Trading off wages and job satisfaction

Second, we consider the wage that would make a worker at a job with state \( s = (a, w, \psi_L) \) indifferent between that job and a job with higher job-satisfaction, \( s' = (a, w', \psi_H) \). That is, we compute the function \( w^*(a, w) \) that satisfies

\[
W(a, w^*(a, w), \psi_H) = W(a, w, \psi_L)
\]

We compute \( w^*(a, w) \) as function of \( w \) for \( a = 0 \) and \( a = 50,000 \) and plot these as solid lines in Figure 17. Comparing these wages can be thought of as analogous to the indifference relationships derived in the theoretical model in Section 6 and Figure 7. Results for the estimated model are plotted in solid lines. We repeat the exercise under zero search costs (\( \kappa = 0 \) and \( \bar{\kappa} = 0 \)) and plot these in dashed lines.

The first take-away from Figure 17 is that the function \( w^*(a, w) \) lies below the 45°-line: a worker with a low satisfaction worker with zero assets and an annual wage of $20,000 will accept a high satisfaction job with an annual wage of around $12,500. In this sense the high satisfaction job is valued at $7,500 in annual wages to the worker.

Second, as the wage of the low satisfaction worker increases, so does the pay-cut that the worker is prepared to take in moving to a high satisfaction job. At higher wages the worker is already in an
Figure 17: Wage offer indifference across assets and wages

income position to build up insurance against job-loss, and has a lower marginal utility of consumption. In this position the worker cares less about monetary compensation and has a higher marginal value of job satisfaction, so is prepared to take a larger pay-cut to move into a higher-satisfaction.

Third, for a given wage a high asset worker is prepared to take a larger pay-cut than a low asset worker. This replicates the theoretical result from Section 6: higher assets tilt the worker's job acceptance policy away from wages and towards job satisfaction.

Fourth, the gap between the pay-cuts acceptable to low and high asset workers narrow as wages increase. This is because the probability of job separation is low and so a high wage worker with low assets will - with high probability - quickly be able to increase their assets, so their job acceptance behavior comes to approximate that of a high asset worker.

Finally, with zero search costs the acceptable pay-cuts are larger. With no search costs the worker can search every period. Importantly they can freely search again once in a high satisfaction job. Workers then take even larger pay-cuts knowing that they can search again for free in the future. The gap is larger for the high asset worker since during his future search in the high satisfaction job he can accommodate a lower wage and supplement his consumption through drawing down on his assets.

Overall these conclusions are consistent with those in Section 6 and provide strong evidence for the quantitative value of job-satisfaction, in many cases the worker is prepared to take a pay-cut of around 50 percent.

Search decisions

The previous two exercises to an extent ignored the search decision of the worker, first assuming the worker was already searching and second allowing a free transition. Now we quantify how the satisfaction level of a job affects the search behavior of a worker. Recall that the conditional mean effects of wages and satisfaction on search are fitted in our indirect inference estimation - matching the parameters of the linear probability model $S_i = \alpha + \beta_w w_i + \beta_\psi \psi_i$, here we extend the analysis to include the effect of assets. For a given value of $\kappa$ and states $(a, \psi)$ we can determine the threshold reservation wage for search $w(a, \psi)$ such that for all $w < w(a, \psi)$ the individual searches. That is $w(a, \psi)$ equates the marginal benefit of search to the marginal
cost as follows

\[
W(a, w(a, \psi), \psi) - \int \max \{W(a, w(a, \psi), \psi), W(a, w', \psi')\} dF(w', \psi') = \frac{\kappa}{\lambda E}
\]

We compute \(w(a, \psi_L)\) and \(w(a, \psi_H)\) for the mean value of \(\bar{\kappa}\). Results are plotted in Figure 18

First note that for both levels of job satisfaction the reservation wage for search is declining in assets. For asset values over $60,000, no high satisfaction worker searches at \(\bar{\kappa}\) since they can no longer find higher satisfaction jobs and the value of search in terms of wage outcomes does not outweigh the cost. As the wage and asset levels of the worker fall, workers search more as predicted by the theory. The main difference in search behavior, however, is due to the satisfaction of the worker in their current job. Taking workers with assets of $20,000: only high satisfaction workers in jobs paying less than around $14,000 search, while the cut-off wage for low satisfaction workers is around $27,000.

13 Robustness - Ability and debt

What happens if the ability of the worker is correlated with their initial level of debt? This was precisely the problematic source of endogeneity that we controlled for in Section 5 by using variation in debt that was orthogonal to individual unobservables. Let’s call this unobservable ability \(a_i\) and suppose that it is positively correlated with wages. The positive and significant coefficient on debt in the 2SLS wages specification compared to an insignificant negative coefficient under OLS would imply that ability and debt are negatively correlated. Still one may be concerned that these average effects miss important differences across the distribution of debt and ability. The limited sample size makes approaches such as quantile regressions impossible in our case but we can get some intuition for the effect of debt and ability from the model. In particular, one may be concerned that the model loads all of the responsibility for the positive correlation between wages and debt into our search and selection mechanism. If ability is positively correlated with debt then the mechanism will have less work to do.

We modify the model to allow for a correlation between debt and ability to account for these concerns.
We also note that Yannelis (2015) suggests that the correlation with debt \( \delta_t = \operatorname{corr}(a_{i,t}, d_{i,t}) \) has changed from positive to negative over time. In his words “debt was negatively selected in the 1980s when default costs were low, and is advantageously selected in the 2000s following increases in non-repayments costs”. We can therefore think of our experiment as considering the effect of different policies under these selection regimes.

We remind the reader that our estimation of the model only on the sample students without debt makes this a perfectly valid experiment to consider.\(^{38}\)

We modify the model as follows. We assume that students are of five fixed ability types \( \{a^k_i\}_{k=1}^5 \), and the wage \( w_{i,j} \) of worker \( i \) at firm \( j \) is the product of ability and firm productivity \( z_j \). Conditional on job-satisfaction type, productivity is log-normally distributed. In the population distribution we therefore have

\[
\operatorname{var}(\log w_i) = \operatorname{var}(\log a_i z_i) = \operatorname{var}(\log a_i) + \operatorname{var}(\log z_i).
\]

We further assume that (i) \( \log a_i \in \{-2\Delta, -\Delta, 0, \Delta, 2\Delta\} \) with equal probability giving \( \operatorname{var}(\log a_i) = 2\Delta^2 \), (ii) the mean and variance of the resulting population distribution of wages is the same as estimated in Section 8 for each satisfaction type, (iii) ability accounts for \( \phi \) percent of the variance of wage offers. Together these imply that \( \log z_i \sim \mathcal{N}(\mu_k, (1-\phi)\sigma_k^2) \) and \( \Delta = \sqrt{\phi\sigma_k^2/2} \) for \( k \in \{L, H\} \). In the simulated model we assumed that \( d_i \sim \mathcal{N}(\mu_d, \sigma_d^2) \), we now assume that conditional on ability \( d_i | a_i \sim \mathcal{N}(a_i^\gamma \mu_d, \sigma_d^2) \), so that if \( \gamma < 1 \) then \( \operatorname{corr}(d_i, a_i) < 0 \) and if \( \gamma > 1 \) then \( \operatorname{corr}(d_i, a_i) > 0 \). Since there is a one-to-one relationship between \( \gamma \) and the \( \operatorname{corr}(d_i, a_i) \) we consider the correlation directly without reporting \( \gamma \). We set \( \phi = 0.20 \) in line with the contribution of ability to the variance of wages in Bagger et al. (2014).\(^{39}\)

More to be added.

### 14 Conclusion

In this paper we have provided a number of results. We first showed empirically that the level of student debt held by a graduating college student has a statistically significant effect on early labor market behavior and outcomes. Specifically we find that higher levels of debt cause workers to end up in jobs with higher wages, lower job satisfaction and to search more on the job. We showed that these outcomes can be neatly rationalized by a simple extension of the Lise (2013) model of search with asset accumulation to accomodate a degree of non-pecuniary disutility of work. Since wages and asset levels are linked through the budget constraint whereas job satisfaction is not, higher levels of debt cause workers to substitute higher wages for lower job satisfaction in their reservation policies. We then went on to extend this simple model to a quantitative framework which is estimatable using the novel observables provided by the NCES BB08 data. We found a quantitatively important role for job satisfaction in shaping the labor market behavior of individuals and strong evidence for its interaction with asset levels. Imposing the exact institutional framework of US student loans in 2008 we showed that the model’s out-of-sample predictions for students with student debt fits well with the data, recommending the model for policy analysis. In this version of the paper we considered a simple policy experiment of a transition to a income based repayment scheme (IBR).

The IBR is strictly preferred by students with higher debt burdens as it allows student to intertemporally

\(^{38}\)Conditional on the introduction of ability not effecting the estimated moments from workers without debt. The particular way in which we introduce ability is designed to ensure that this is the case.

\(^{39}\)See their variance decomposition of wages over job-experience displayed in Figure 9. We take our value of \( \phi \) from those with education in 15-20 years. At two years of work variance in ability is around 0.02 and the variance in wages 0.06 giving \( \phi = 0.30 \). As experience grows so does the variance in wages while variance in wages due to ability is constant, as a bound \( \phi \approx 0.20 \) at 30 years experience.
shift large repayments to periods when the marginal utility of consumption is lower. For students with low debts the existing policy environment is preferred. When averaging across the empirical distribution of debt and assets we found that the policies were essentially tied in terms of average welfare although a median voter would prefer the IBR.

This paper can be extended along a number of dimensions. In particular, as detailed in Appendix C, the quantitative model in section 7 can easily be extended to accommodate college choice. Such a model would use the continuation values in the existing model as data, utilizing the new College Scorecard data to estimate probabilistic production functions for colleges, and be simply estimated in a discrete choice framework. Such a setting would allow policy experiments of the type: “Suppose the repayment policy changed from $R$ to $R'$, what is the total effect on welfare, including debt take up and college choice?” rather than being qualified by our statements at the beginning of section 11.

First, given the large and increasing levels of student debt in the U.S. a robust and estimated partial-equilibrium model of how debt effects labor market behavior seems like a necessary first step, and which we hope we have provided in this paper. Secondly we hope to recommend job satisfaction and its interaction with worker balance sheets as a quantitatively important consideration for welfare and decision making in economic models of labor market behavior.
References


### A Additional tables

**Table 5: Summary Statistics**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
<th>Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>A. 2000 cohort</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>0.393</td>
<td>0</td>
<td>0.488</td>
<td>0</td>
<td>1</td>
<td>11,698</td>
</tr>
<tr>
<td>GPA</td>
<td>319</td>
<td>322</td>
<td>48.83</td>
<td>0</td>
<td>400</td>
<td>9,879</td>
</tr>
<tr>
<td>Cumulative debts ($000)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unconditional</td>
<td>14.19</td>
<td>11.63</td>
<td>15.70</td>
<td>0</td>
<td>150</td>
<td>10,024</td>
</tr>
<tr>
<td>Conditional</td>
<td>20.22</td>
<td>17.76</td>
<td>15.15</td>
<td>0.1</td>
<td>150</td>
<td>7,033</td>
</tr>
<tr>
<td>Salary ($000)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unconditional</td>
<td>27.28</td>
<td>27</td>
<td>22.50</td>
<td>0</td>
<td>500</td>
<td>9,230</td>
</tr>
<tr>
<td>Conditional</td>
<td>31.57</td>
<td>30</td>
<td>21.23</td>
<td>0.1</td>
<td>500</td>
<td>7,978</td>
</tr>
<tr>
<td>General satisfaction</td>
<td>0.854</td>
<td>1</td>
<td>0.354</td>
<td>0</td>
<td>1</td>
<td>8,089</td>
</tr>
</tbody>
</table>

| **B. 2008 cohort**         |        |        |           |     |     |      |
| Male                       | 0.414  | 0      | 0.493     | 0   | 1   | 15,048 |
| GPA                        | 333    | 338    | 45.38     | 0   | 400 | 15,048 |
| Cumulative debts ($000)    |        |        |           |     |     |      |
| Unconditional              | 18.55  | 16.16  | 18.91     | 0   | 150 | 15,048 |
| Conditional                | 25.22  | 21.13  | 17.82     | 0.1 | 150 | 11,067 |
| Salary ($000)              |        |        |           |     |     |      |
| Unconditional              | 27.12  | 26.00  | 23.26     | 0   | 250 | 15,048 |
| Conditional                | 33.29  | 31.00  | 21.41     | 0.008| 250 | 12,260 |
| General satisfaction       | 0.732  | 1      | 0.443     | 0   | 1   | 12,273 |

**Note:** “Unconditional” indicates full sample, while “conditional” restricts the sample to only individuals with positive debts or salaries.
# B BB questions

The following table gives the precise mapping between the variables we consider and the questions asked in the BB03 and BB08 surveys. In all cases these questions are consistent over time.

Table 6: B&B Questionnaire

<table>
<thead>
<tr>
<th>Variable</th>
<th>BB</th>
<th>Definition / Question</th>
</tr>
</thead>
<tbody>
<tr>
<td>Duration</td>
<td>$d_i$</td>
<td>As of the 2009 interview, the number of weeks after the respondent began applying for jobs that the respondent received the offer for the job currently held</td>
</tr>
<tr>
<td>Number of jobs</td>
<td>$j_i$</td>
<td>How many jobs have you had since you graduated from your 2007-08 bachelor’s degree-granting institution?</td>
</tr>
<tr>
<td>Search</td>
<td>$S_i$</td>
<td>Are you currently looking for a different job?</td>
</tr>
<tr>
<td>Income</td>
<td>$y_i$</td>
<td>Annual income from all sources</td>
</tr>
<tr>
<td>Borrowing</td>
<td>$D_i$</td>
<td>Indicates the cumulative amount borrowed from all sources for the respondent’s undergraduate education through June 30, 2008</td>
</tr>
<tr>
<td>Parental income</td>
<td>cincome</td>
<td>Indicates the total 2006 income of parents of dependent respondents. Used in the federal need analysis to determine aid eligibility for the AY 07-08.</td>
</tr>
<tr>
<td>Influence</td>
<td>b1lninfl</td>
<td>Has the amount of student loan debt you have from your undergraduate education influenced your employment plans and decisions in any way?</td>
</tr>
</tbody>
</table>

**Job satisfaction**  

<table>
<thead>
<tr>
<th>Question</th>
<th>Response</th>
</tr>
</thead>
<tbody>
<tr>
<td>Are you satisfied with each of the following in your current job …</td>
<td>b1jbay</td>
</tr>
<tr>
<td>… Compensation (pay and fringe benefits)?</td>
<td></td>
</tr>
<tr>
<td>… Importance and challenge of your work?</td>
<td>b1jbimpo</td>
</tr>
<tr>
<td>… Overall would you say that you are satisfied with your job?</td>
<td>b1jbover</td>
</tr>
<tr>
<td>… Job security?</td>
<td>b1jbsecr</td>
</tr>
<tr>
<td>… Would you prefer to work more hours than you do?</td>
<td>b1preft</td>
</tr>
<tr>
<td>… Do you consider your job to be part of a career you are</td>
<td>b1carind</td>
</tr>
<tr>
<td>… pursuing in your occupation or industry?</td>
<td></td>
</tr>
</tbody>
</table>
C Introducing a college debt / school decision

Here we consider an extension of the model to allow for endogenous education, college and debt choice. We also show how we would estimate and identify this model. The key idea is that given continuation values from the problem described in Section 7, the college choice decision can be modeled as a static discrete choice for which we can apply all of the standard econometric tools for estimating such models via maximum likelihood.

This extension would allow us significantly expand the scope of applicability of our work. By modeling the endogenous debt decision we are able to ask questions such as: How does the composition of borrowers in terms of skill and repayment ability, and overall college attendance, change with changes in \( R \) rather than the limited frame of reference discussed at the start of Section 11.

C.1 Econometric model

Individuals leave high school and then choose to enroll in college or not. Upon leaving high-school the individual’s state is a level of skill \( s_i,0 \), a level of assets \( a_i,0 \), a vector of observed characteristics that relate to college choice \( \mu_i \), and an unobserved disutility of college \( \eta_i \).

Those that do not enroll in college enter unemployment immediately with value \( U(a_i,0) + \delta' \Pi_i \) where \( \Pi_i \) contains observed individual variables choose a college \( c \in \mathcal{C} = (1, \ldots, C) \). To accommodate skills we modify the problem from Section 7. Searching workers draw job bundles \( (z, \psi) \sim F(z, \psi) \) where \( z \) is match productivity. Wages reflect skill according to a function \( w(s, z) \).\(^{40}\) From this problem we would derive \( U(a, d, s) \) - the present value of unemployment augmented for skill.

Individuals that choose to enroll in college suffer disutility \( \eta_i \) and then draw a vector of iid preference shocks \( \varepsilon_i = (\varepsilon_1, \ldots, \varepsilon_C) \) distributed according to a generalized extreme value distribution.

Definition 5. A college \( c \) is a tuple \( \Omega_c = \{ \phi_c, x_c, h_c, \xi_c, X_c \} \) where

1. \( \phi_c \) is the observed cost of attendance. Students leave college as an unemployed worker with assets \( a'_{i,c} = \max \{ 0, a_i,0 - \phi_c \} \) and student debt \( d'_{i,c} = \min \{ 0, a_i,0 - \phi_c \} \).

2. Students enter the labor market with skills \( s' \) which are drawn from the transition function \( h_c : s_0 \times [\underline{s}, \bar{s}] \to [0, 1] \). This function gives a probability distribution over post-college skills \( s' \sim h_c(s', s_0) \) for each \( s_0 \).

3. \( x_c \) is the observed level of consumption during college according to the student budget.

4. \( \xi_c \) is an unobserved (to the econometrician) permanent utility of attending college \( c \).

5. \( X_c = [X_{c,1}, X_{c,2}] \) is a vector of observed college-level components and consists of two parts. \( X_{c,1} \) is valued in utility terms the same way across individuals (such as amenities, size, teacher-student ratios).

   The effects of \( X_{c,2}^2 \) are valued in a way that depends on observable student characteristics \( \mu_i \).

6. While at college a student’s non-random utility from attendance is parameterized as follows

\[
W_{i,c} = \xi_c + \gamma_1 X_{c,1} + \gamma_2 g(\mu_i, X_{c,2}) + \sum_{t=0}^{4} \beta^t \log(x_c)
\]

\(^{40}\)Given observed wages and skill we would be able to estimate a flexible specification for \( w(s, z) \) and distributions for \( z | \psi_k \) as in the estimation of the model described in section 8.
where the function $g$ would combine elements of $\mu_i$ and $X_c^2$ depending on the variables.\footnote{For example if $\mu_i$ is the location of the high-school of the student and $X_c^2$ is the location of the college then $g \left( \mu_i, X_c^2 \right)$ could be an indicator that the college is out of state or a measure of distance.}

The high school graduate’s problem is as follows

$$\max \left\{ U(a_{0i}, 0, s_{0i}) + \delta^* \Pi_i , -\eta_i + \int \max_{c \in C} \left\{ W_i,c + \varepsilon_{i,c} + \beta^5 \int_s^2 U(a_{i,c}', d_{i,c}', s') h_c(s', s_{i,0}) ds' \right\} dg(\varepsilon_{i,c}) \right\}$$

$a_{i,c}' = \max \{ 0, a_{i,0} - \phi_c \}$

$d_{i,c}' = \min \{ 0, a_{i,0} - \phi_c \}$

Note that given our solution of the previous model and a functional form for $h_c(s', s)$ we can treat the expected post-college value of unemployment $U_{i,c}^e = \beta^5 \int_s^2 U(a_{i,c}', d_{i,c}', s') h_c(s', s_{i,0}) ds'$ and the pre-college value of unemployment $U_i = U(a_{0i}, 0, s_{0i})$ as data. Let $\bar{V}_{i,c} = W_{i,c} + U_{i,c}^e$. With this notation the problem can be written

$$\max \left\{ U_i + \delta^* \Pi_i , -\eta_i + \bar{V}_i \right\} , \text{ where } \bar{V}_i = \int \max_{c \in C} \left\{ \bar{V}_{i,c} + \varepsilon_{i,c} \right\} dG(\varepsilon_{i,c})$$

Given the extreme-value assumption on $\varepsilon_{i,c}$ and our computation of $\bar{V}_{i,c}$ we can compute $\bar{V}_i$ in closed form

$$\bar{V}_i = \sum_{c=1}^{C} \frac{\exp \left( \bar{V}_{i,c} \right)}{\sum_{c=1}^{C} \exp \left( \bar{V}_{j,c} \right)} \times \bar{V}_{i,c}$$

C.2 Estimation

Leveraging our data the estimation sample would include the following observables on the individual and college level: \{ $a_{0i}, s_{0i}, \mu_i, c_i \} \}_{i=1}^{n}$ and \{ $\phi_c, x_c, X_c \} \subset C$ where the data from individuals is from BB08 and for colleges is from the CSC. The variable $c_i$ is an indicator of attendance at college $c$. Estimation would proceed in two stages, (i) estimating the exogenous transition function $h_c(s', s)$, (ii) estimate the utility parameters $\gamma_1, \gamma_2, \xi_c$ and distribution of $\eta_i$.

First stage In the first stage we estimate the functions $w(s, z)$ and $h_c(s, s_{0i})$. Treating $s_{1,0}$ as high-school SAT score and $s_{1}'$ as an interaction of school quality and GPA we could form an estimate of $h_c$ under some mild parametric assumptions. For example

$$\log s_{1}' \sim \begin{cases} \delta_c + \alpha_s \log s_{1,0} + \alpha_X X_c + \nu_i, & \nu_i \sim N(0, \sigma_\nu) \text{ w.p } 1 - p^d_c(s_{1,0}) \text{ (Completion)} \\ \log s_{1,0} & \text{ w.p } p^d_c(s_{1,0}) \text{ (Dropout)} \end{cases}$$

where $(\delta_c, \alpha_s, \alpha_X, \sigma_\nu)$ and a probit for $p^d_c$ can be estimated using the College-Scorecard data.\footnote{The College-Scorecard data has measures of 10th, 25th, 50th, 75th and 90th percentile SAT scores of entering cohorts in each university and measures of the same percentiles of earnings of students at 6, 7, 8 and 10 years after college completion, as well as measures of the probability of non-completion}
\(\eta_i \sim N(0, \sigma_\eta)\). The individual choice probability is then
\[
p_i(\theta) = \int \mathbb{P} \left[ \text{Attend college c} \mid \eta_i \right] dG(\eta_i)
= \int \mathbb{P} \left[ \text{Attend college} \mid \eta_i \right] dG(\eta_i) \times \mathbb{P} \left[ \text{Choose college c} \right]
= \mathbb{P} \left[ \bar{V}_i - (U_i + \delta^*\Pi_i) \geq \eta_i \right] \times \frac{\exp \left( \bar{V}_{i,c} \right)}{\sum_{j=1}^C \exp \left( \bar{V}_{j,c} \right)}
\]
\[
p_i(\theta) = \Phi \left( \frac{\bar{V}_i - (U_i + \delta^*\Pi_i)}{\sigma_\eta} - \left[ \omega_0 + \omega_a a_{0,i} + \omega_s s_{0,i} \right] \right) \times \frac{\exp \left( \bar{V}_{i,c} \right)}{\sum_{j=1}^C \exp \left( \bar{V}_{j,c} \right)},
\]
where \(\Phi(x) = 1 - \int_0^x \frac{1}{\sqrt{2\pi}} \exp \left( -\frac{u^2}{2} \right) du\).

In a second case we can allow for and estimate the correlation between \(\eta_i\) and observed states \((a_{0,i}, s_{0,i})\). This is of particular interest since Galipolli, Meghir and Violante (2014) estimate a negative correlation between psychic costs of college and assets, arguing that this is required to explain the low attendance rates of low asset individuals given the high returns to college. We specify that \(\eta_i \sim N(\mu_\eta(a_{0,i}, s_{0,i}), \sigma_\eta(a_{0,i}, s_{0,i}))\) stipulating some simple functions for \(\mu_\eta(\cdot)\) and \(\sigma_\eta(\cdot)\). Consider \(\mu_\eta(s, a) = \omega_0 + \omega_s a + \omega_s s\) and \(\sigma_{\eta, i} = \sigma_\eta\).

\[
p_i(\theta) = \Phi \left( \frac{\bar{V}_i - U_i - \delta^*\Pi_i - [\omega_0 + \omega_a a_{0,i} + \omega_s s_{0,i}]}{\sigma_\eta} \right) \times \frac{\exp \left( \bar{V}_{i,c} \right)}{\sum_{j=1}^C \exp \left( \bar{V}_{j,c} \right)}.
\]

The parameters estimated in the second stage are therefore \(\theta = (\mu_\eta(\cdot), \sigma_\eta(\cdot), \xi_c, \gamma_1, \gamma_2)\) and the log-likelihood is
\[
\mathcal{L}(\theta) = \sum_{i=1}^n \left[ \log \Phi \left( \frac{\bar{V}_i - U_i - \delta^*\Pi_i - [\omega_0 + \omega_a a_{0,i} + \omega_s s_{0,i}]}{\sigma_\eta} \right) \right] + \log \left( \frac{\exp \left( \bar{V}_{i,c} \right)}{\sum_{j=1}^C \exp \left( \bar{V}_{j,c} \right)} \right).
\]

This allows us to separately estimate \((\xi_c, \gamma_1, \gamma_2)\) using a standard logit regression in which \(U_i^c\) (through \(\bar{V}_{i,c}\)) is a control. Despite the fact that we only have data on students that entered college we can still estimate \((\omega_0, \omega_a, \omega_s, \sigma_\eta, \delta)\) via simulated maximum likelihood. For each \(i\) we can simulate the probability of college attendance by taking \(S\) draws of \(\eta_i \sim N(\omega_0 + \omega_a a_{0,i} + \omega_s s_{0,i}, \sigma_\eta)\) and computing the simulated choice probability \(\tilde{p}_i = \frac{1}{S} \sum_{s=1}^S 1 \left[ \bar{V}_i - (U_i + \delta^*\Pi_i) \geq \eta_s \right]\). We then choose \((\omega_0, \omega_a, \omega_s, \sigma_\eta, \delta)\) to maximize the simulated log-likelihood \(\tilde{L}(\theta) = \sum_{i=1}^N \log \tilde{p}_i\). Alternatively this could be estimated using the NLSY97.

C.3 Including the instrument

The extended model is highly flexible and can be used to explicitly include the instrument used in Section 5. Let \(g_{i,c}\) denote grants. If \(a_{1,0} = 0\) then the following identity must hold: \(d_{i,c} = \phi_{i,c} - g_{i,c}\). Suppose that the university has a policy that the loan-grant ratio is \(Z_c = g_{i,c} / (g_{i,c} + d_{i,c})\) for every student. This then implies that
\[
d_{i,c} = \left[ 1 - \frac{Z_c}{1 - Z_c} \right]^{-1} \phi_{i,c}.
\]

We can now solve the model under the observed changes in \(\{Z_c\}_{c=1}^C\) assuming all other parameters are held constant. Our instrument will be validated if the covariance of student debt with skills does not change substantially within each school.\(^{43}\)

\(^{43}\)This could be examined by a plot of \(\Delta \text{cov}_{i,c} (s_{1,i,c}, d_{i,c})\) against \(\Delta Z_c\).
D Additional work on instrument
E Further descriptive statistics

E.1 Debt to income ratios across institutions

A recent issue raised in policy has been the growth in enrollments at private for-profit colleges. A conjecture has been that these institutions have been associated with high debt and low incomes due to negative selection into the school on ability and low teaching standards. The BB08 data allows us to study this proposition more carefully. Figure 19 shows - by type of institution - the distribution of debt to income ratios of employed graduates. The mean is somewhat higher for students coming from for-profit schools, however not drastically so. These distributions are conditional on employment and positive debt, but we find that the unconditional employment rates out of institution types are also similar: 82.5% for public schools, 81.0% for private non-profit and 83.7% for private for-profit colleges. When conditioning on positive debt, the rates of employment are around 3% higher for all types of schools, an observation consistent with our theoretical model.

Figure 19: Type of Institution and Debt Burdens

![Graph showing distribution of debt to income ratios by type of institution.]

Note (i) BB08 data restricted to students with positive borrowing and positive income.

Figure 19 can also be used to gauge the percentage of lifetime income that student debt represents. To find an upper-bound on this rate consider the following calculation. Suppose that over a 40 year career income growth is certain and equal to the interest rate. Then if we divided the x-axis by 40 we would be plotting the distribution of the ratio of debt to present discounted lifetime income. To find an upper-bound consider the following calculation. Suppose that over a 40 year career income growth is certain and equal to the interest rate. Then if we divided the x-axis by 40 we would be plotting the distribution of the ratio of debt to present discounted lifetime income. The total fraction of college students with debt exceeding one percent of lifetime income would be around five percent. Under a permanent income model labor market decisions would be based on lifetime income and the difference in debt-to-income ratios between for profit and non-profit schools should be near zero.

\[^{44}\text{The present discounted dollar value of lifetime income if the initial wage } w_0 \text{ grows at a constant rate } g \text{ is } V = \sum_{t=0}^{40} \beta^t (1 + g)^t w_0. \text{ In 25 to 40 year olds the annual real rate of growth in mean incomes is around 8% so } 1 + g = 1.08 > 1/\beta \approx 1.04 \text{ when } \beta \text{ is set to match the risk-free rate of return. Hence our statement that setting } \beta = (1 + g)^{-1} \text{ delivers an upper-bound.}\]

\[^{45}\text{Obviously income growth may be correlated with institution type but here we simply see to get an idea of the magnitudes involved.}\]
E.2 Debt and parental income

We find that there is a strong dependence of debt on parental income. As a first pass and as a preface to the issues involved with isolating the effect of student debt on labor market decisions, we consider the following exercise. We estimate the following equation on our BB08 estimation sample

$$\log Debt_{i,j} = \gamma_j + \beta X_i + \varepsilon_{i,j}. $$

We control for university fixed effects $\gamma_j$ and individual observables $X_i$ which include a quadratic in age, dummies for race and gender and the student budget submitted by the university to the government for individual $i$’s course of study.\footnote{46} Note that even in this simple regression the BB data allow us to control for confounding issues such as high debt due a university being costly ($\gamma_j$, which implicitly controls also for university type) or a course being particularly expensive. In 20 we plot the densities of the estimated residuals $\hat{\varepsilon}_i$ comparing the residuals for students whose total parental income is in the bottom 10% of incomes, the middle of the income distribution, and the top 10% of incomes. Clearly residual debt is higher for students of lower parental income. Adding dummies for income quintiles to the regression we find that debt among students of parents in the top income decile is 23 per cent lower than students of bottom decile parents.\footnote{46}\footnote{The student budget is the sum of tuition and living expenses which include board, food and educational supplies as well as the costs of other amenities. It is an annual measure and agreed between the college and Federal loan programs.} Note that we do not a priori expect this pattern. If low income parents are low ability and have low ability children, then the willingness of those children to borrow will be lower. Here we seem to observe a different force, students of low income parents have less financial support from the home so borrow more to fund their education. This exercise makes clear the importance of controlling for the correlation of unobserved ability and debt in our exercise of Section 5.

Figure 20: Parental Income and Debt

Note: Residuals are those from a regression of log cumulative borrowing on institution fixed efecte and controls for age, gender, race and student budget. The regression is estimated on students with positive debt, we find that including a correction term for selection into positive debt (inverse Mills ratio dervied from a probit model using the same controls and estimated on the entrie sample) does not effect the figure significantly.


F Proofs

F.1 Section 6

Proof. (Proposition 1)

(i) Existence of continuous $h(a, \psi)$. Since $W$ is continuous and increasing in $w$ and $\psi$ then the cut-off rule implicitly defines a continuous function $h : \mathcal{A} \times \Theta \to W$, such that for a given level of assets $a$ and a draw of a job $(w, \psi)$, the agent accepts the job if $w > h(a, \psi)$

(ii) $h(a, \psi)$ strictly decreasing in $\psi$. This is due to the trade-off between wages and job-satisfaction induced by the monotonicity of utility in both $w$ and $\psi$. Fixing $a$ consider a $(w, \psi)$ such that $W_a(w, \psi) = U_a$. Due to monotonicity and continuity of $W$, if we were to decrease $\psi$ by $\varepsilon$ then we would need to increase $w$ by some amount $\varepsilon'$ to maintain the equality with $U_a$. This implies $h_a(\psi)$ is strictly decreasing.

(iii) $h(a, \psi)$ strictly convex in $\psi$. The proof is due to the concavity of $u(c)$ and $v(\psi)$. For a given $a$, $W_a(w, \psi)$ is concave in $w, \psi$. Suppose that $W$ were linear in $w$, and consider a decrease in $\psi$ of $\varepsilon$. Due to the concavity of $W$ in $\psi$ the wage must change by a larger amount when compensating for the $\varepsilon$ decrease in $\psi$. If $W$ is also concave in $w$, then this effect is compounded and an even larger increase in $w$ is required to leave utility unchanged.

Proof. (Proposition 2)

Intuitively, the proof is due to the fact that assets are linked to wages via consumption but not linked to non-wage utility. Consider a decrease in the level of wealth from $a$ to $a' < a$. For now hold the value of unemployment constant. For a given level of $\psi$ the worker will now reject the same set of offers as before and additionally reject more low wage jobs. Due to the concavity of $W$ this will be most pronounced at high $w$, low $\psi$ jobs. In the limit as $\psi \to \bar{\psi}$ and $w \to \underline{w}$, the Inada conditions on $u$ and $v$ imply that this effect becomes zero as small decreases in the wage lead to very large decreases in utility. This results in a clockwise rotation of the function $h$. Now consider the fact that the value of unemployment also decreases since $U''(a) > 0$. This decreases both the wage and non-wage utility necessary to coax a worker out of unemployment, shifting $h$ down and to the left. Combined this implies that $h(a', \psi) > (\leq)h(a', \psi)$ for very large (small) values of $\psi$. 

\[\square\]