Rethinking College Financing: Wealth, College Majors, and Macroeconomic Consequences*

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Abstract

This paper studies the aggregate and distributional implications of college subsidies (e.g.: Pell grants) expansion by explicitly considering college major choice in general equilibrium. First, I empirically document that majors chosen by poorer students exhibit higher initial earnings, lower earnings growth, and lower earnings risk. I then build a general equilibrium heterogeneous agent life-cycle model with uninsurable idiosyncratic risk and borrowing constraints calibrated to the U.S. economy. Calibration suggests that majors chosen by poorer students also have higher disutility. Quantitatively, I find that unconditional expansion in college subsidies is *not* sufficient to induce poorer students to switch into the majors that richer students are currently choosing. Keeping the total subsidies spent equalized across experiments, college subsidies conditional on majors currently chosen by the poor (e.g.: STEM, Health, Education) generate higher average welfare gains than unconditional or conditional subsidies on majors currently chosen by the rich.

Keywords: credit constraint, higher education spending, college majors, inequality
JEL codes: E24, H52, I22, I23, J24, O15.

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1 Introduction

The United States is experiencing a higher education affordability crisis. Pell grants, the largest source of grants in the United States, covers only 20-30% of college cost nowadays, compared to more than 70% in the 1980s (U.S. Department of Education (2018)). This leaves many students with huge burdens of debt upon graduation.

College major choice is an important human capital investment decision, yet unexplored in macroeconomic studies of college financing policies. Most research either focuses on the extensive margin of college vs. non-college (Restuccia and Urrutia (2004), Lochner and Monge-Naranjo (2012), Abbott et al. (2019)), or differences among college selectivity (Capelle (2020)). However, college major is at least as important as a source of heterogeneity as college types. First, much of the human capital at college is specific and developed through majors. Second, college major shapes labor market prospects or even locks students into particular careers[1]. In fact, using administrative data from Norway, Kirkeboen, Leuven and Mogstad (2016) find that the effect on earnings from major is *stronger* than the effect from attending a more selective institution. Incorporating college majors while rethinking college financing is also relevant for the policy circle, as a growing number of leading universities[2] in the U.S. have indeed started practicing differential tuition pricing by majors.

This paper explores the aggregate and distributional implications of college financing policies by explicitly considering college major choice in general equilibrium. My paper makes three main contributions. The first two contributions lie in understanding how wealth shapes college major choices, both empirically and quantitatively. College financing policies are obviously related to wealth. Therefore, understanding the determinants of major choices of poorer students helps interpreting the results of the policy experiments. More specifically, I combine several micro data sources (NLSY97, ACS, PSID) to empirically document sorting patterns into majors by parental income, and assess the *qualitative* relationship between various earnings characteristics[3] and sorting by poorer vs. richer students. I then develop a general equilibrium heterogeneous agent life-cycle model to *quantify* three relevant determinants[4] for sorting. The quantitative model is disciplined by the empirical results. The third contribution is to use the calibrated model as a laboratory to study the macroeconomic consequences of college subsidies, comparing

[1] 40% of students regret their choice of major because it locks them into careers they do not want to pursue (Federal Reserve Board of Governors (2022)).

[2] Including, but not limited to Indiana, Michigan, Minnesota, Ohio State, Rutgers, Wisconsin.

[3] The three earnings characteristics I consider empirically are: earnings profile, lifetime earnings, and earnings risk.

[4] These three determinants are: earnings profile, earnings risk, and non-pecuniary value of the majors.

subsidies that are unconditional or conditional on majors in general equilibrium[5].

What types of majors are poorer students more likely to choose? Empirically, I show that students with lower-income parents sort into majors such as STEM (Science, Technology, Engineering, Mathematics)/Health/Education. Richer students sort into majors such as Business/Social Sciences/Arts/Biology. The majors that poorer students choose have flatter earnings-age profile (i.e. higher initial earnings, lower earnings growth) and lower earnings risk. I document these facts both at finer major level (for 14 majors, with non-college as major 0, full list in Appendix A.1) and coarser level (for 3 broad college major groups). I use the National Longitudinal Survey of Youth 97 (NLSY97) as my main data source, and complement it with the American Community Survey (ACS) and the Panel Study of Income Dynamics (PSID).

At the finer level, I leverage the large sample size of the ACS and estimate earnings regressions to compute major-specific earnings characteristics. I find that poorer students sort into majors with higher initial earnings, lower earnings growth, and lower earnings risk. To summarize sorting into majors by parental income, I estimate a multinomial logistic regression of college major choice on parental income and proxies of imputed potential earnings across majors. Imputed potential earnings deal with selection on earnings potential. The multinomial logistic regression allows me to form a measure of choice elasticity for each major, which captures the change in the likelihood of choosing a major as parental income increases. I find a strong negative correlation between major choice elasticity and initial earnings, a strong positive correlation between major choice elasticity and earnings growth/earnings risk. However, there is not much correlation between major choice elasticity and lifetime earnings. These results highlight the need to move beyond expected earnings to explain the sorting patterns of poorer vs. richer students by considering aspects such as earnings profile and earnings risk.

I complement the finer level evidence with additional measures of earnings profile and earnings risk at coarser level using the PSID, and obtain similar qualitative relationships. Empirical findings at coarser level serve two purposes. First, they complement the suggestive evidence on sorting at the finer level. Compared to the cross-sectional measures of earnings characteristics derived from the ACS, these additional measures emphasize the life-cycle nature of earnings characteristics. Second, I use these empirical results to discipline the quantitative life-cycle model.

[5] There are two broad categories of college financing policies: grants or loans. I focus on college subsidies, which are essentially grants. In particular, I examine college subsidies distributed to students from the bottom quartile only, as well as college subsidies distributed to all students. The former captures the idea of Pell grants, whereas the latter corresponds to tuition pricing policies (e.g.: free tuition). Abbott et al. (2019) consider both grants and loans. Others (e.g.: Luo and Mongey (2019), Matsuda and Mazur (2022), Murto (2022)) focus on student debt repayment schemes (fixed repayment vs. income-based repayment).

Because of the smaller sample size of the panel data and concern for the curse of dimensionality in the quantitative analysis, I group majors and occupations into coarser bins. Due to the lack of information on college majors in the PSID, I estimate the earnings profile and compute the earnings risk of the most likely occupation corresponding to each college major group. I use the variance of log (residual) earnings and the standard deviation of log (residual) earnings as my baseline measures of earnings risk. I find that consistent with the finer level evidence, poorer students sort into majors whose most likely occupations exhibit flatter earnings profile and lower earnings risk.

Motivated by the empirical evidence, I build a general equilibrium heterogeneous agent life-cycle model under incomplete markets which embeds three relevant determinants for sorting: earnings profile, earnings risk, and non-pecuniary value for each major. Differences in the non-pecuniary values of each major are essential to match the major shares as in the data. Markets are incomplete: individuals are subject to uninsurable idiosyncratic shocks and borrowing constraints. The model is solved in general equilibrium: it is closed by a balanced government budget and a final goods Cobb-Douglas production technology on capital and labor, with labor being a composite over occupations.

The two key decisions of the individual are: college major choice and career (occupation)[6] choice upon graduation. Major choice is a risky and partially irreversible human capital investment decision. Individuals pay a fixed college cost if they choose to attend college. College cost may be subsidized by the government. Major choice is risky as individuals face two types of uncertainty while making their decision: uncertainty on occupational choice and uncertainty on (realized) earnings in their chosen occupation. The former uncertainty stems from individuals not observing their initial occupational talent nor do they know their non-pecuniary occupational taste while choosing their college majors. The latter is due to the fact that individuals receive income subject to uninsurable idiosyncratic risk along their working life. Individuals also make consumption and saving decisions each period, and their income is subject to progressive taxation while working.

Major choice is partially irreversible as each major develops different kinds of human capital. To capture this idea in a succinct way, I model major as a human capital technology that increases human capital in each occupation by a certain amount. The level of increase varies across major $\times$ occupation pairs, because majors develop specific human capital. As a result, the initial human capital of a specific occupation is drawn from a distribution that depends on

[6]This is what I call occupation in this paper. I assume that the occupational choice is made once and for all. I use occupation and career interchangeably.

the major the individual graduates from, which differs in terms of the mean. This property of the majors affects the total supply of human capital, and consequently the level of average tax rate that is needed to balance the government budget.

I calibrate the model to the U.S. economy in three steps. One key estimate from my calibration is that majors currently chosen by poorer (richer) students also have negative (positive) non-pecuniary value. More specifically, I first assign some parameters to their standard values. I then calibrate the occupation-specific income process, by first directly estimating some parameters from the data, and then by using the minimum distance estimator to match key moments on earnings to determine the rest. Finally, I use Simulated Method Moments (SMM) to match salient moments from the data to obtain values for the remaining parameters. The variances of earnings by majors and occupations, as well as major and occupational shares, are particularly useful moments in the calibration.

I use the calibrated model to explore (i) the quantitative importance of the three determinants (i.e. earnings profile, earnings risk, non-pecuniary value) of major choice, and (ii) the sorting patterns, as well as the aggregate and distributional consequences of college subsidies, unconditional or conditional on majors. College subsidies are distributed only to students from the bottom quartile of the initial wealth distribution. This configuration is in line with Pell grants in the U.S., which target low-income students. In robustness and extensions, I consider college subsidies distributed to all students, which can be conceptualized as tuition policies.

I find that lower earnings risk is the most quantitatively important determinant for poorer students' current major choice, followed by non-pecuniary value. More specifically, I set each determinant one-by-one to the average value (across occupation for earnings profile and earnings risk, across major for non-pecuniary value), and compare how the major shares of bottom quartile students change relative to the baseline, where all three elements are at play. I find that under the baseline, students from the bottom quartile are 12% more likely to sort into STEM/Health/Education than the overall major share. After setting earnings risk of each occupation to the average value, these poorer students are only 6% more likely to sort into these majors than the overall share.

My policy experiments suggest that an expansion in (unconditional) college subsidies is not sufficient to induce poorer students to switch into the majors originally taken by the rich. This is in contrast with the intuitive view that college financing policies alleviate poorer students' financial burden, thereby inducing them to choose majors currently taken by the rich. The reason is simple. A college subsidy has two roles. First, it directly reduces the college cost. This is a pure income effect and applies to all forms of college subsidies, unconditional or conditional. Conditional subsidy has an additional role. It changes the relative prices between majors and the expected value of each major. My finding implies that the pure income effect of college subsidies is not sufficient for poorer students to sacrifice the front-loaded labor earnings profile and earnings risk for more enjoyable majors. Choosing a major that leads to a more front-loaded labor earnings profile and low earnings risk career allows low-wealth individuals to better build up their buffer stock of savings under incomplete markets.

Keeping the total spending in college subsidies equalized across experiments, I find that average welfare is the highest for conditional subsidies on STEM/Health/Education (0.94 percent in consumption equivalent values), compared to unconditional subsidies (0.83 percent) or conditional subsidies on Business/Social Science/Arts/Biology (0.64 percent). This result is mainly due to the larger increase in human capital from majoring in STEM/Health/Education compared to Business/Social Science/Arts/Biology in most careers. Conditional subsidies on STEM/Health/Education incentivize more students to choose these majors. As a result, aggregate human capital increases the most under conditional subsidies on STEM/Health/Education, thereby reducing the average tax rate that is needed to balance the government budget.

Welfare gains are not distributed equally across initial wealth groups. College subsidies yield the highest average welfare gains for individuals at the bottom quartile of the initial wealth distribution, whereas the other three quartiles incur average welfare losses. For the bottom quartile, conditional subsidies on STEM/Health/Education lead to higher average welfare gains (4.50 percent) than unconditional subsidies (3.83 percent) or conditional subsidies on Business/Social Science/Arts/Biology (3.26 percent). The other three quartiles incur welfare losses due to lower equilibrium occupational wages in high-skill occupations and lower equilibrium interest rate. Welfare loss is partly compensated by the fall in average tax rate.

The rest of the paper is organized as follows. Section 2 summarizes the related literature. Section 3 describes the empirical results. Section 4 presents the model. Section 5 explains the parameterization, followed by quantitative results in Section 6. I discuss robustness and extensions in Section 7. Section 8 concludes and suggests avenues for future work.

2 Related Literature

This paper contributes to the literature on credit constraints in education, in particular in higher education. Most research on the macroeconomic effects of college financing focuses on the extensive margin of college vs. non-college (Restuccia and Urrutia (2004), Lochner and

Monge-Naranjo (2012), Abbott et al. (2019)). However, this masks substantial differences among college students. For those who focus more on the differences within college students, the emphasis is on differences in college types (Capelle (2020), Athreya and Eberly (2021)). This paper emphasizes the role of college majors as a key source of heterogeneity within college students. In fact, using administrative data from Norway, Kirkeboen, Leuven and Mogstad (2016) find that the effect on earnings from major is *stronger* than the effect from attending a more selective institution. Altonji, Blom and Meghir (2012) argue that the gap in average wage between engineering and education majors are almost as large as the gap between college and high school graduates.

Methodologically, this paper is closest to the literature in macroeconomics using micro data to study macro implications on issues related to human capital and inequality, as in Abbott et al. (2019), Capelle (2020), Agostinelli et al. (2022), Boar and Lashkari (2022), Boerma and Karabarbounis (2021), Daruich (2022), Fuchs-Schündeln et al. (2022), Fujimoto, Lagakos and VanVuren (2022), Hurst, Rubinstein and Shimizu (2022), and Kim, Tertilt and Yum (2022) just to name a few.

This paper also speaks to the vast literature on socioeconomic background and human capital choice (Galor and Zeira (1993), Bell et al. (2019), Chetty et al. (2020), Hsieh et al. (2019)). Cameron and Heckman (2001) highlight the importance of differences in pre-college human capital by socioeconomic background in affecting the extensive margin of college attendance. I focus on the interaction between wealth and incomplete markets for the intensive margin of college major choice. Several papers study how student debt upon graduation affects occupational choice or job choice (Ji (2021), Luo and Mongey (2019), Folch and Mazzone (2022), Matsuda and Mazur (2022)). The type of college financing policies I consider is in the form of grants. While student debt-related college financing policies may induce poorer students to switch into majors originally taken by the rich (Murto (2022)[7]), my quantitative findings suggest that it is not the case for grant-related college financing policies such as Pell grants or free tuition. Alon et al. (2022) show that college graduates with large student debt choose occupations with higher initial earnings and lower returns to experience. In their paper, human capital accumulation is subject to Ben-Porath with on-the-job skill investment. In my paper, human capital process is estimated from the data and subject to uninsurable idiosyncratic risk. I also formalize the link between college majors and occupations (career)[8]. Boar and Lashkari (2022) explore how individuals with richer/poorer parents choose occupations with different

[7]These include policies (for income-based debt repayment schemes) such as lowering the repayment amount as a fraction of income, capped interest capitalization, and shorter repayment period.

[8]Lemieux (2014) provides an empirical exploration of the relationship between college majors and occupations. I structurally model the relationship and take it to the data for quantitative analysis.

non-pecuniary values and study the implication of this channel for intergenerational mobility of welfare. My empirical analysis at the finer major level borrows from their methodology. However, I incorporate both the pecuniary and non-pecuniary aspects of college majors and study the macroeconomic implications of college subsidies. Not many papers have examined how socioeconomic background affects college major choice, with the exception of Sloane, Hurst and Black (2021) on gender and Patnaik, Wiswall and Zafar (2021), who call for more work on sorting into majors by parental income. I contribute by documenting a comprehensive set of facts on this question.

Lastly, this paper is related to the literature on the determinants (Arcidiacono (2004), Arcidiacono, Hotz and Kang (2012), Wiswall and Zafar (2015), Altonji, Arcidiacono and Maurel (2016), Abramitzky, Lavy and Segev (2022)) and returns to college major choice (Altonji, Blom and Meghir (2012), Altonji and Zimmerman (2019), Bleemer and Mehta (2022)). I add to this literature by moving beyond the average earnings of majors, and highlight the life-cycle aspects of earnings (earnings profile, earnings risk). More importantly, I consider how wealth interacts with these characteristics and shapes one's major choice. My paper brings a macroeconomic, general equilibrium perspective on the choice of college majors and policy implications[9].

3 Empirics

In this section, I provide empirical evidence on how poorer/richer students sort based on three earnings characteristics (i.e.: earnings profile, lifetime earnings and earnings risk) of the majors. First, I describe the data sources. Second, I document sorting patterns at finer major level. Third, I discuss why and how to classify majors and occupations into coarser groups. Fourth, according to my baseline grouping of the majors and occupations, I present additional facts on earnings profile and earnings risk of the major's most associated occupation.

3.1 Data

The main data used in the empirical analysis is the National Longitudinal Survey of Youth 1997 (NLSY97), which I complement with two other sources: the American Community Survey (ACS) and the Panel Study of Income Dynamics (PSID). The ACS is used for analysis at finer level (14 majors, including non-college, and 22 occupations) and classification of majors and occupations into coarser groups. The PSID is used for analysis at coarser level (3 majors, including non-college, and 3 occupations).

[9]Patnaik (2020) studies differential tuition pricing at the University of Wisconsin-Madison. Murto (2022) studies the impact of income-based student debt repayment schemes on major choice.

NLSY97. The NLSY97 is a nationally representative longitudinal survey of youths aged 12-16 as of December 31 1996 (hence born in 1980-1984). Each individual is interviewed annually from 1997 to 2011, and biannually from 2013 to 2019. All nominal variables are converted to real by the 2012 Personal Consumption Expenditure (PCE) index. I use annual income from wages and salaries as my main variable for labor earnings. The data contains information on parental income, Armed Forces Qualification Test (AFQT)[10] score, college majors and occupations. I use average parental income up to age 18 as a proxy for the individual's initial wealth. AFQT is my main measure of pre-college human capital. I follow the approach described in Altonji, Bharadwaj and Lange (2019) to construct AFQT scores that are comparable across cohorts. College major is defined as the individual's final major observed in the data. In order to capture the idea of career, occupations are defined as the most frequently held occupation since the individual is done with her education. Appendices A.1 and A.2 display the classification of 13 majors and 22 occupations respectively. This classification ensures comparability across data sources. Due to the lack of sufficient observations, I drop observations with pre-law and interdisciplinary studies majors. I focus on four-year college students and exclude hispanic/latino/black oversample to avoid selection issues. I also remove outliers by dropping individuals with employment history in the military, self-employed, or have parental income and annual labor earnings at the top and bottom 0.1% and 0.25% respectively. One shortcoming of the NLSY97 is its length. Individuals in the sample were born in 1980-1984; hence, it is not possible to obtain earnings information of their entire life-cycle. To address this, I complement the NLSY97 with the PSID.

ACS. I use the ACS for years 2009-2019 as the ACS only starts to contain information on college majors (i.e. field in which the individual received a Bachelor's degree) since 2009. The large sample size of the ACS ensures sufficient observations even at finer major-occupation level, which allows me to compute major characteristics for each of the 13 majors. I adjust all nominal variables by the 2012 PCE index. I use hourly wage as my main variable for earnings, but perform robustness checks with annual wage income. Moreover, the major-occupational share information is useful for classifying occupation into coarser groups, which serve as a basis for the quantitative analysis. Similar to the NLSY97, I drop individuals with employment history in the military, self-employed, or with hourly wage at the top and bottom 1%. I focus on individuals of working age (25-64).

PSID. The PSID is a nationally representative panel of more than 18,000 individuals living in 5,000 families in the United States. I use the sample from 1968-2013. The panel structure of the PSID makes it ideal for estimating life-cycle income processes and constructing life-cycle

[10]Most interviewees took the AFQT test in the first round of the survey. AFQT measures the cognitive skills (in maths and verbal) of the interviewees.

earnings measures. However, the PSID does not contain information on college majors. To overcome this issue, I formalize the link between majors and occupations. Sample selection follows the standard procedure. I restrict the sample to the head of the household. I also exclude households from the Survey of Economic Opportunity sample (low-income supplemental sample), individuals with employment history in the military, self-employed, as well as observations with top-coded or top and bottom 1% pre-tax labor earnings.

3.2 Sorting patterns at finer level

I follow a three step procedure to understand which college major characteristics are related to the sorting patterns of poorer vs. richer students at finer level. First, I use a multinomial logit model to compute the major choice elasticity of each major using the NLSY97. Major choice elasticity is defined as the percentage increase in the probability of choosing a major if the student's parental income increases by 1%. Therefore, a positive (negative) implies that the major is more likely to be chosen by a richer (poorer) student. Second, I construct major characteristics using the ACS. I focus on three characteristics related to earnings: earnings profile (initial earnings and earnings growth), lifetime earnings, and earnings risk. Third, I examine the correlation between each major's earnings characteristics and choice elasticity.

Major choice elasticity. I estimate a multinomial logit model of college major choice. There is concern that students may self-select into a major that they are better at. For example, some majors may be more cognitive-intensive (so that AFQT is more important in these majors), while others may be more intensive in social skills (Deming (2017)). It is also possible that parental network is more important in certain majors such as business (Kramarz and Skans (2014)). To deal with this concern, I impute potential earnings of an individual in each major. More specifically, I run an earnings regression on race, gender, marital status, years of schooling, U.S. born dummy, household size, 5-year age group dummies, region fixed effect, cohort fixed effect, year fixed effect, and most importantly, normalized AFQT and parental income. I show in Appendix A.3 that using the AFQT is sufficient to capture pre-college human capital differences between the rich and the poor. I then compute the predicted earnings for each major, given individual characteristics.

In order to compute the major choice elasticity, I run two separate multinomial logit regressions, one with imputed log potential earnings and another one without. The key right-hand side variable in both regressions is log parental income. Major choice elasticity is defined as:

$$\frac{\partial \ln P(m_i = k)}{\partial \ln \bar{y}} = \beta_k^{\bar{y}} - \sum_{k'=1}^{13} P(m_i = k')\beta_{k'}^{\bar{y}} \tag{1}$$

where $\beta_k^{\bar{y}}$ is the coefficient on log parental income for major k, estimated from the multinomial logit regression.

I use major choice elasticities estimated from the multinomial logit regression with imputed potential earnings as my baseline measure. Figure 1 displays the results. Richer students choose majors such as Communication, Arts, Social Science, Business, or Biology, whereas poorer students tend to major in STEM (Science, Technology, Engineering, Maths), Health and Education. Appendix A.3 suggests that richer students score higher at AFQT. As STEM and Health majors are typically more intensive in cognitive skills, lower AFQT reduces the probability of poorer students choosing these majors. Therefore, controlling for self-selection strengthens sorting.

In what to follow, I report the correlation between earnings characteristics and major choice elasticity, estimated both with and without controlling for imputed potential earnings. I show that correlations do not change much across these two different measures of major choice elasticity, implying that much of the sorting patterns *cannot* be explained by differences in pre-college human capital.

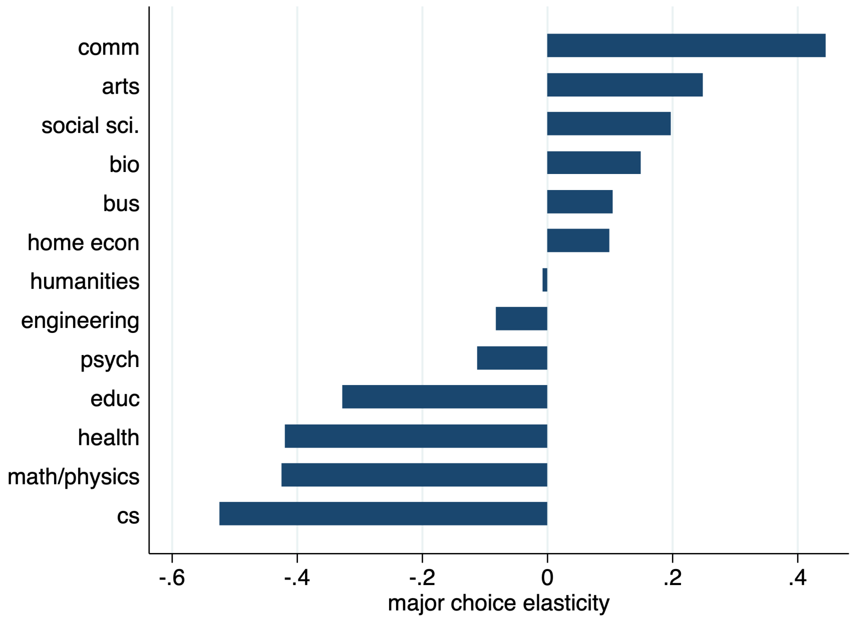


Figure 1: Major Choice Elasticity

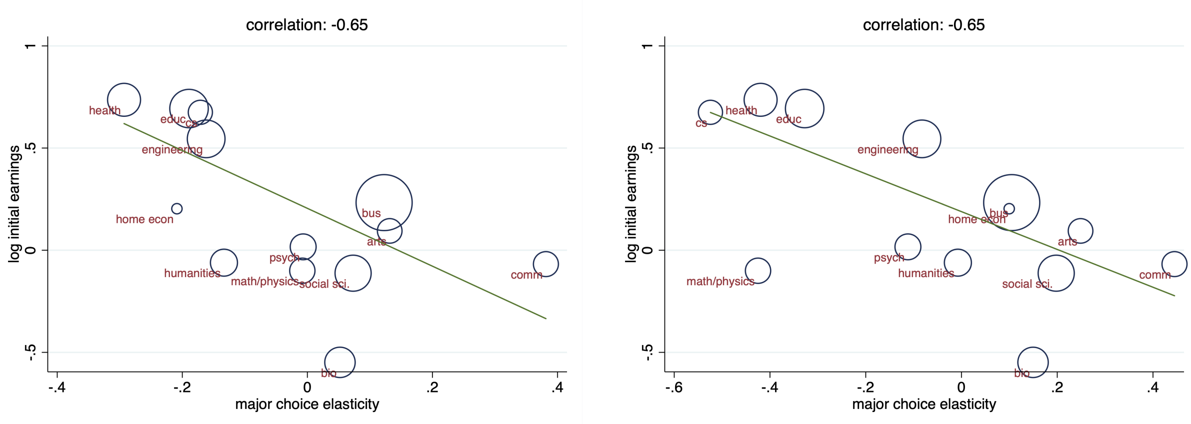
Notes: Each bar represents the estimated major choice elasticity (x-axis) from a multinomial logit regression controlling for major-specific imputed potential earnings. A negative (positive) value implies that the major is chosen by poorer (richer) students.

Earnings profile. I run the following earnings regression:

$$\ln y_{it} = \alpha + \beta\Gamma_{it} + \lambda_{1m} \times m_i + \lambda_{2m} \times m_i \times age_{it} + \lambda_{3m} \times m_i \times age_{it}^2 + \delta_t + \epsilon_{it} \tag{2}$$

where y_{it} is the hourly wage of individual i in year t[11]. Γ_{it} are demographic characteristics such as race, gender, marital status, years of schooling, and U.S. born dummy. m_i is an indicator which equals to 1 if major m is chosen by i. δ_t is the year fixed effect. λ_{1m} captures log initial earnings of major m. The returns to experience of major m ($\lambda_{2m} + 2 \times age \times \lambda_{3m}$) is non-linear as age squared enters the regression. I report the returns to experience (earnings growth) at the age 25.

There is a strong negative relationship between initial earnings and major choice elasticity (Figure 2), and a strong positive relationship between earnings growth and major choice elasticity (Figure 3), implying that poorer students sort into majors with higher initial earnings and lower earnings growth.



(a) no control (b) + potential earnings

Figure 2: Initial Earnings vs. Sorting

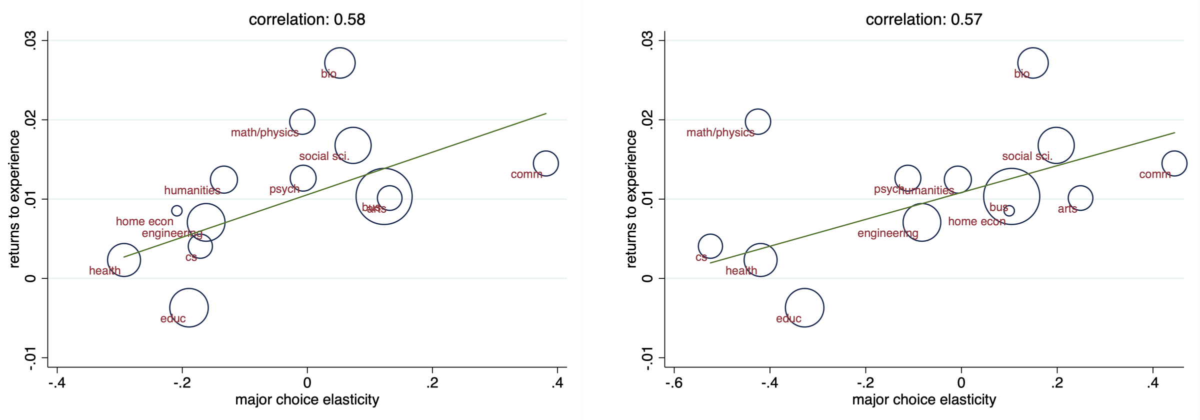
Notes: Panel (a) and Panel (b) show the correlation between log initial earnings (λ_{1m}, y-axis) and major choice elasticity (x-axis). Major choice elasticity is estimated without controls in Panel (a) and with controls on imputed potential earnings in Panel (b). Negative (positive) value of major choice elasticity implies that poorer (richer) students are more likely to choose the major. Size of the circle indicates the share of students in that major.

Lifetime earnings. I follow a Deaton-Hall[12] type specification:

$$\ln y_{ict} = \alpha + \beta\Gamma_{it} + \sum_{a \in A} (\phi_{am} \times m_i) + \gamma_c + \delta_t + \epsilon_{ict} \tag{3}$$

[11] All findings on sorting patterns are robust to using annual labor income as the main variable for earnings.

[12] To address collinearity, I impose the restriction that time dummies are orthogonal to time trend. The time effects thus capture only cyclical fluctuations.



(a) no control

(b) + potential earnings

Figure 3: Earnings Growth vs. Sorting

Notes: Panel (a) and Panel (b) show the correlation between earnings growth ($\lambda_{2m} + 2 \times 25 \times \lambda_{3m}$, y-axis) and major choice elasticity (x-axis). Major choice elasticity is estimated without controls in Panel (a) and with controls on imputed potential earnings in Panel (b). Negative (positive) value of major choice elasticity implies that poorer (richer) students are more likely to choose the major. Size of the circle indicates the share of students in that major.

where A denotes a set of 5-year age bins, {25-29, 30-34, ..., 60-64}. ϕ_{am} is the main coefficient of interest, which essentially captures the average log earnings of major m in age bin a. γ_c denotes the (birth) cohort fixed effect.

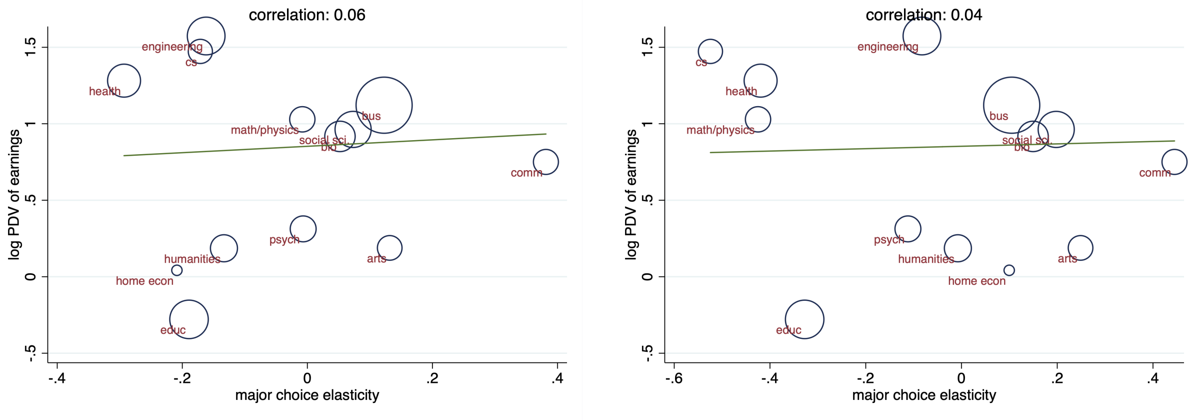
Lifetime earnings is computed as the Present Discounted Value (PDV) of ϕ_{am}:

$$PDV_m = \sum_{a=1}^{Na} \left(\frac{1}{(1+r)^5} \right)^{a-1} \phi_{am} \tag{4}$$

where $r = 0.04$ is the discount rate, $N_a = 8$ is the number of age bins.

Figure 4 reveals no obvious relationship between lifetime earnings and sorting. This result is robust to alternative values of r[13]. The little correlation between lifetime earnings and major choice elasticity implies that one should probably move beyond expected earnings to explain the sorting patterns of poorer vs. richer students by considering aspects such as earnings profile and earnings risk.

[13] As discussed in Guvenen et al. (2022), there is no obvious choice of the discount rate r. Whether human capital should be discounted at the risk-free rate or at higher, long-term risky asset rate is not an obvious question. Moreover, compared to financial assets, human capital is also not tradable. I use 0.04, which is a standard long-run equilibrium risk-free interest rate as my baseline value. I also experiment with $r = 0$ and $r = 0.08$, the correlations remain close to 0 (equal to (-0.01, -0.04) and (-0.05, -0.07) respectively).



(a) no control (b) + potential earnings

Figure 4: Lifetime Earnings vs. Sorting

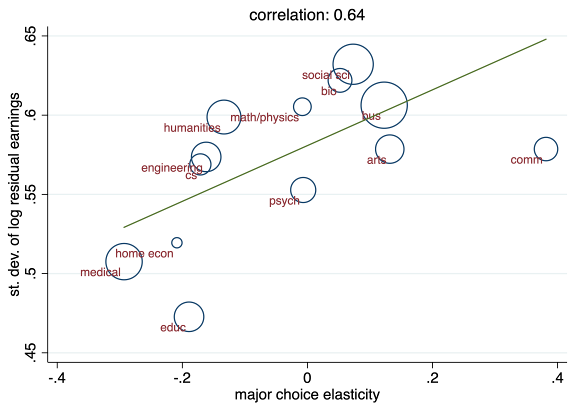
Notes: Panel (a) shows the correlation between lifetime earnings (y-axis) and major choice elasticity (x-axis). Negative (positive) value of major choice elasticity implies that poorer (richer) students are more likely to choose the major. Size of the circle indicates the share of students in that major.

Earnings risk. I use the standard deviation in log residual earnings in each major from earnings regression in (3) as a proxy for earnings risk. This measure is not unreasonable if we consider a student at the time of choosing a major, who has not yet realized her income path. I use the panel data and life-cycle earnings information to construct alternative measures of earnings risk in Section 3.4 and Appendix A.11. Figure 5 suggests that poorer students sort into lower earnings risk majors.

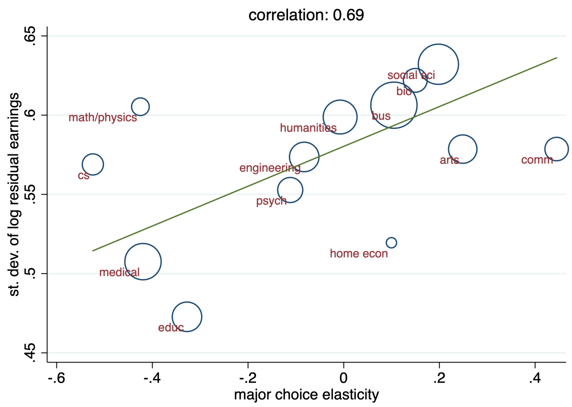
Specificity. In Appendix A.7, I document additional sorting patterns of students based on the major's specificity. A more specific (as opposed to general) major means that students in that major develop human capital (or skills) that are less widely applicable across occupations (i.e.: students develop less transferable human capital). As earnings capture the value of skills, specificity is also an earnings characteristic. I find a strong negative correlation between major specificity and major choice elasticity.

How is specificity measured? Intuitively, the more unequal earnings are across occupations for a given major, the more specific this major is. My finding implies that poorer students are more likely to be "locked in" by their major choice[14]. Appendix A.7 discusses the construction of major specificity and the sorting pattern in more detail.

[14] Lock-in need not necessarily be bad. On the one hand, stronger lock-in implies that students are forgoing the flexibility of occupational choice, and a major that develops more general human capital provides insurance against occupation choice uncertainty. On the other hand, if a major equips students extremely well in certain occupations, realized earnings are higher.



(a) no control



(b) + potential earnings

Figure 5: Earnings Risk vs. Sorting

Notes: Panel (a) shows the correlation between earnings risk (y-axis) and major choice elasticity (x-axis). Negative (positive) value of major choice elasticity implies that poorer (richer) students are more likely to choose the major. Size of the circle indicates the share of students in that major.

To sum up, I find that poorer students sort into majors with higher initial earnings, lower earnings growth, and lower earnings risk. Lifetime earnings is not the determining factor for sorting. The above results are obtained using earnings characteristics constructed from the ACS. The advantage is that we can uncover sorting patterns of the majors at finer level. However, one shortcoming is that the ACS is not really a panel, but earnings profile and earnings risk are life-cycle earnings characteristics. Therefore, in what to follow, I use estimates on major characteristics from this section to group majors into broad clusters and provide additional results at coarser level using the PSID.

3.3 Classification of majors and occupations

I classify majors and occupations into coarser groups, mainly for two reasons. First, reducing the number of majors and occupations can help overcome the curse of dimensionality in the computation of the quantitative model. Second, coarser major and occupation bins ensure sufficient observations for each major-occupation pairs in the panel data.

Clustering of majors. Using estimates on major choice elasticity and earnings characteristics[15], I apply K-means clustering to group the 13 majors (excluding non-college) into 3 broad

[15] Earnings characteristics include: log initial earnings, returns to experience, log PDV of lifetime earnings, standard deviation of log residual earnings, Gini specificity, standard deviation of occupational earnings premia. The latter two variables are related to the concept of major specificity.

clusters. K-means is a non-parametric approach to classify objects (in this context, majors) with similar characteristics into the same cluster. Details on the major clusters and their characteristics are in Appendix A.8. More specifically, cluster 1 is comprised of majors in STEM and Health. These majors are typically chosen by poorer students, have higher lifetime earnings, higher initial earnings, lower earnings growth, and lower earnings risk. Cluster 2 is comprised of majors such as Business, Social Sciences, and Biology. These majors also have higher lifetime earnings, but they have a steeper earnings profile and higher earnings risk. Cluster 3 is comprised of low lifetime earnings majors such as Arts, Humanities, and Education.

One key observation is that cluster 3 seems redundant: there is no clear sorting in major cluster 3 (see Tables A.3 and A.4 in Appendix A.8) and no clear relationship between lifetime earnings and sorting (see Figure 4 in Section 3.2). Therefore, I further split majors in cluster 3 into cluster 1 or 2 based on another K-means for cluster 3. In particular, I apply K-means again to cluster 3 and divide it into two groups. I then assign each group in cluster 3 into either cluster 1 or cluster 2 based on the within-group average characteristics.

The left column of Figure 6 shows the baseline grouping of majors. There are 3 broad majors including no college, which is indexed by $m = 0$. $m = 1$ refers to STEM (Science, Technology, Engineering, Maths), Health and Education. It is the major group that poorer students sort into. $m = 2$ (e.g.: Business, Social Science, Communication, Arts, Humanities, Biology, Psychology) is chosen by richer students.

To simplify notation, I refer to each broad major group as "major".

Occupation groups. I use the 3 majors derived above and employ a share-based classification scheme using relative major share as my measure, defined as the occupation-specific major share scaled by the overall major share in (5). The scaling is necessary to account for the fact that certain majors (e.g.: home economics) may be inherently smaller than other majors (e.g.: social science):

$$\text{relative major share} = \frac{\text{occupation-specific major share}}{\text{overall major share}} = \frac{N_{mj}/N_j}{N_m/N} \tag{5}$$

where N is the number of observations.

More specifically, for each of the 22 occupations, I first restrict the sample to U.S. born white males to reduce potential confounding factors due to gender, race, or cultural background. For each occupation, I sort major clusters based on their relative major share. I then assign the occupation the same index as the major cluster with highest relative major share. For example, for occupation "sales", the major cluster with the highest relative share is 2, so occupation "sales" belongs to occupation group 2. Appendix A.9 lists the occupation groups. The grouping is highly robust, regardless of whether age is restricted to 22-35 only, with or without non-college workers, or whether the sample is restricted to bachelor's only. I define occupation group i as the typical occupation of major cluster i.

Baseline grouping. Figure 6 shows the baseline grouping of majors and occupations, which I will use in the subsequent empirical analysis and the quantitative model. From now on, to simplify notation, I refer to broad major group as "major" and occupation group as "occupation".

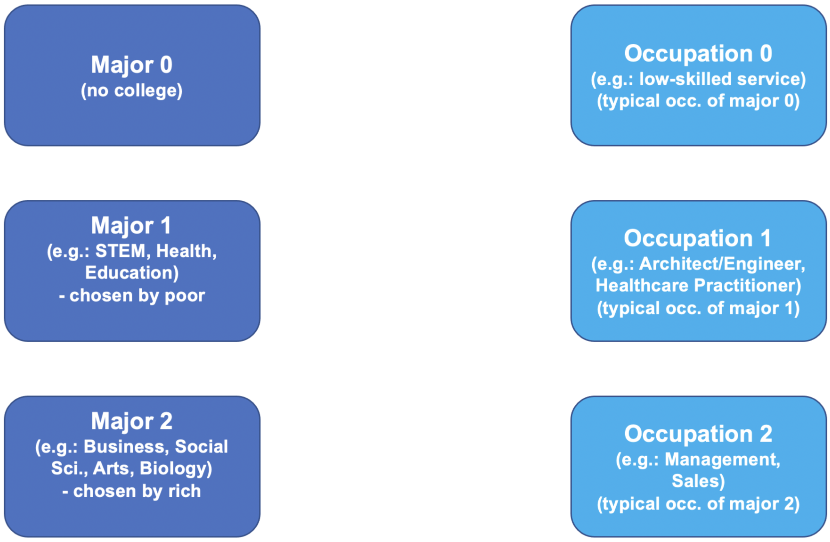


Figure 6: Baseline Grouping of Majors and Occupations

I have already discussed majors. As for occupations, occupation 0 is mainly comprised of low-skilled service occupations. Non-college workers ($m = 0$) are the main labor suppliers in these occupations. Occupation 1 mainly contains finer-level occupations corresponding to major 1, such as architect/engineer, computer/mathematical, health practitioner/technician, installation/maintenance/repair - just to name a few. Consistent with intuition, occupation 1 is the typical occupation of major 1. Occupation 2 is the typical occupation of major 2, which includes business/financial operations, management, sales, office/administration etc.

Table A.5 in Appendix A.1 and Table A.6 in Appendix A.2 summarize the characteristics of majors and occupations. Compared to major 2, major 1 (i.e.: the majors that poorer students tend to choose) has higher initial earnings, lower returns to experience, lower standard deviation of residual earnings (proxy for earnings risk), and higher specificity. 39% of college students choose major 1. The lifetime earnings of major 1 is only slightly higher than major 2. As to occupations, occupation 1, the most likely chosen occupation of major 1, has the highest lifetime earnings and lowest standard deviation of residual earnings.

Major-occupation shares. Table 1 summarizes the relative occupational share for each major, defined analogously as in (5). Unsurprisingly, each major's typical occupation is the most likely occupation of that major. The expression for relative occupational share is given by:

$$\text{relative occupational share} = \frac{\text{major-specific occupational share}}{\text{overall occupational share}} = \frac{N_{mj}/N_m}{N_j/N} \tag{6}$$

	Occ. 0	Occ. 1	Occ. 2
Major 0	1.15	1.04	0.85
Major 1	0.68	1.71	0.75
Major 2	0.60	0.56	1.61

Table 1: Relative Occupational Share by Major

Notes: Each cell in row m column j indicates the relative occupational share of j in major m from the ACS. Table A.7 in Appendix A.10 displays the raw occupational shares by major.

3.4 Sorting patterns with baseline grouping

The earnings measures derived from the ACS are essentially cross-sectional, but earnings profile and earnings risk are life-cycle characteristics. I use the PSID to better capture the life-cycle nature of earnings characteristics. I do not use NLSY97 due to its short duration. As students were born in 1980-1984, we do not yet observe their earnings after age 39. The PSID tracks individuals over their entire career. However, it only contains information on occupations (not college majors). Therefore, I document the earnings profile and earnings risk of each major's typical occupation, because it is the occupation that most of the students of the major will end up with (see Table 1). In particular, I use the PSID to extract the earnings profile (i.e. life-cycle component of earnings) as well as my second measure of earnings risk (see Appendix A.11 for details) in each occupation. I combine the PSID with the NLSY79/97 to compute the second moments of earnings, which constitute my first set of measures for earnings risk.

Sorting patterns. To begin with, I first explore the sorting patterns by parental income under the baseline grouping. This moment is used as key untargeted moment to assess the model's ability to replicate sorting patterns by initial wealth in Section 5.3.

To do so, I define the relative major shares by parental income quartiles analogously as in (5):

$$\text{relative major share in initial wealth group } q = \frac{\text{major share in group } q}{\text{overall major share}} = \frac{N_{mq}/N_q}{N_m/N} \tag{7}$$

This measure captures the extent in which initial wealth group q is more (if the number is above 1) or less (if the number is below 1) likely to choose the major relative to the overall average.

Table 2 summarizes the results. Poorer students are more likely to choose major 0 and major 1, but less likely to choose major 2. As these shares are not conditional on potential earnings (i.e.: not include factors such as AFQT or demographics), it can be viewed as a lower bound on sorting (as discussed in Section 3.2). I use the relative share to adjust for the inherent differences in major size. Raw shares (not adjusted for major size) are reported in Appendix A.12.

	Major 0 (unconditional)	Major 1 (conditional on college)	Major 2 (conditional on college)
Q1	1.43	1.14	0.93
Q2	1.12	1.06	0.97
Q3	0.89	1.00	1.00
Q4	0.55	0.91	1.04

Table 2: Relative Major Shares by Parental Income Quartile

Notes: Each cell represents the relative major share (column 1: unconditional non-college share, column 2: share of major 1 conditional on college, column 3: share of major 2 conditional on college) in parental income quartile in row q.

Earnings profile. I estimate the earnings profile of each occupation by regressing log annual labor earnings on age, age squared and a set of demographic controls, similar to (2). In order to correct for selection into work, I use a Heckman-selection estimator.

Figure 7 plots the age component of earnings by occupation. The yellow line (corresponding to major 2), has a much steeper slope and takes higher values relative to the red line (corresponding to major 1). This indicates that earnings growth is much higher for major 2 than major 1, where major 2 (1) is more likely to be chosen by the richer (poorer) students.

Earnings risk. I compute two sets of earnings risk measures. The first set is related to the second moments of earnings, in the spirit of Guvenen et al. (2021). More specifically, I construct occupation-specific variance of log residual earnings for individuals aged 25-39, as well the standard deviation of log residual earnings growth. I restrict the sample up to 40, as I make

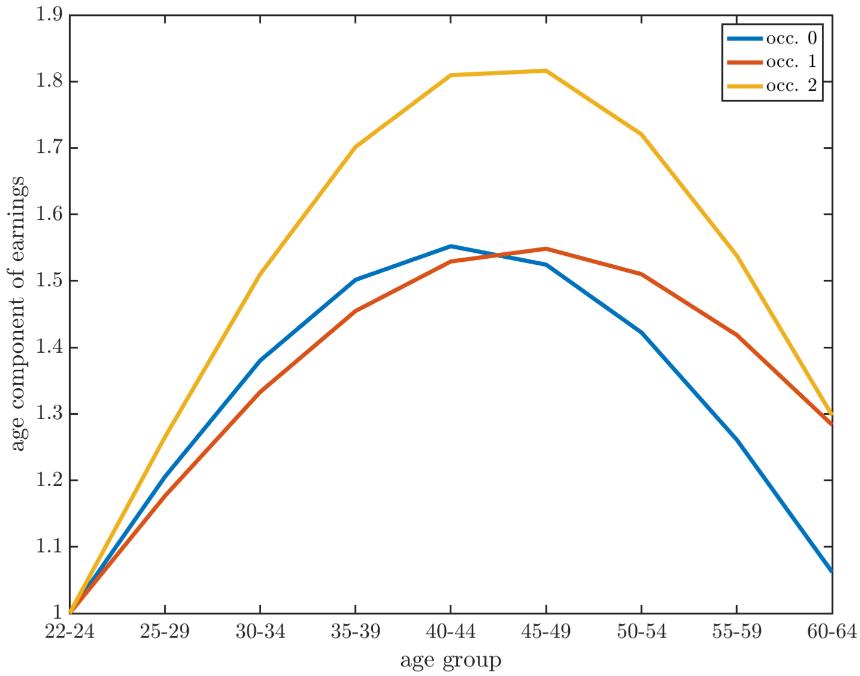


Figure 7: Age Profile by Typical Occupation

Notes: Each line plots the age component (exponential of the coefficients times age and age squared) of earnings by occupation on the y-axis, against 5-year age bins on the x-axis. The red line is the age component of occupation 1, which is the typical occupation of major 1 (i.e.: STEM/Health/Education, majors that are more likely to be chosen by poorer students). The yellow line is the age component of occupation 2, which is the typical occupation of major 2 (i.e.: Business/Social Science/Arts/Biology/Humanities, majors that are more likely to be chosen by richer students). The blue line is the age component of occupation 0, which is the typical occupation of major 0 (i.e. non-college). Table B.1 in Appendix B.3 reports the coefficient estimates on age and age squared.

use of the NLSY79/97 to remove the AFQT component in earnings. Appendix B.3 contains a detailed description of the estimation procedure. The second measure defines earnings risk as the standard deviation of forecast errors of permanent income (re-scaled by expected permanent income to make units of measurement comparable), as in Boar (2019) (see Appendix A.11 for a detailed discussion on this measure).

It is clear from Table 3 that occupation 1 (the most likely occupation for major 1, the major chosen by poorer students), has much lower earnings risk than occupation 2 and 0 (the most likely occupation for major 2 and major 0). As major 1 is more popular among poorer students, this implies that poorer students

	Occ. 0	Occ. 1	Occ. 2
variance of log earnings, age 25-39	0.50	0.36	0.47
st. dev. of log earnings growth	0.63	0.52	0.59

Table 3: Earnings Risk: Second Moments

4 Model

In this section, I build a general equilibrium heterogeneous agent life-cycle model with college major choice, occupational choice, uninsurable idiosyncratic risk and borrowing constraints. The model embeds the three potential determinants for sorting: earnings risk, earnings profile, and non-pecuniary value of majors. The model is then used as a laboratory to (i) quantify the importance of the three determinants for sorting, and (ii) study the sorting patterns, as well as aggregate and distributional consequences of college subsidies, unconditional or conditional on major.

4.1 Environment

Timeline. Figure 8 depicts the life-cycle of an individual. Each period is 5 years. Each individual lives for $T = 12$ periods. They enter the model at the age of 20 ($t = 1$) with heterogeneous initial wealth (a_0) and pre-college human capital (s) drawn from an initial distribution. They die deterministically at the age of 80 ($t = 13$). There are $M = 3$ majors (including non-college, where $m = 0$) and $J = 3$ occupations.

At $t = 1$, individuals observe their major taste shock and decide whether or not to attend college at a cost P_e. The college cost is subsidized at rate g_m for individuals with initial wealth at the bottom quartile. Conditional on college attendance, they choose a major m. If they do not attend college, they draw a vector of occupational talents, one for each occupation (career) j. Upon observing the vector of occupational talents and occupational taste shock, they choose an occupation (once and for all) and start working. If they choose to attend college, they make occupational choice and start working at $t = 2$. Individuals can borrow at interest rate r_b[16] to attend college, but have to repay their student debts under a fixed repayment scheme over 10 years[17] ($t = 2 - 4$). Along their career, individuals face occupation-specific uninsurable idiosyn-

[16] Interest rate on student debt equals to the risk-free rate plus some risk premium (a.k.a. spread). Let r be the annual risk-free rate and ι_b be the spread, then $r_b = (1 + r + \iota_b)^5 - 1$.

[17] One obvious extension is to consider an alternative repayment scheme commonly used in the real world: an income-based repayment scheme over 20 years. However, the fixed repayment scheme is a nice starting point as one can conceptualize refinancing the student debt into risk-free bonds and reduce one extra state variable of student debt (more details in Section 4.2 and Appendix B.1).

cratic income shocks and a borrowing constraint $\underline{a}_m$ each period. They can borrow at a risk-free rate of r. They retire at the age of 65 ($t = 10$), in which case they receive a fraction π of their pre-retirement income and cannot borrow. Finally, they pass a non-negative bequest a_{T+1} to their child upon death.

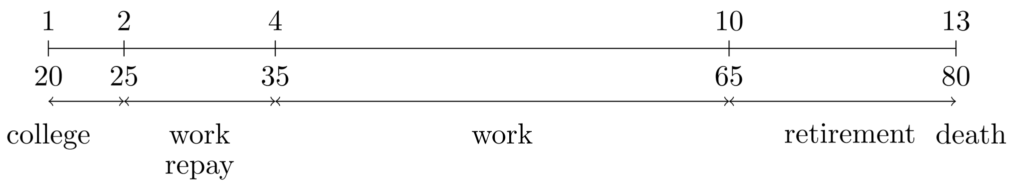


Figure 8: Timeline

The Role of Majors. College majors differ in three ways: college subsidy rate g_m, borrowing constraint $\underline{a}_m$, and increase in occupational human capital $\bar{h}_{mj}$. First, depending on whether college subsidy rates g_m are conditional on major or not, students may pay different prices for college. Second, I assume that the borrowing constraint $\underline{a}_m$ faced by non-college and college workers is different. Third, as will be specified later in the income process section, college major is considered as a human capital technology that boosts human capital in occupation j by a certain amount $\bar{h}_{mj}$, which varies across major $\times$ occupation pairs. $\bar{h}_{mj}$ has two effects on earnings. First, it directly increases human capital within occupation j. Second, $\bar{h}_{mj}$ affects the probability of choosing occupation j given major m, which captures the idea of "lock-in" and specificity, as discussed in Section 3.2 and Appendix A.7.

Preferences. Individuals exhibit warm-glow preferences, in a sense they directly derive utility from passing a bequest to their child. Their lifetime utility is therefore given by:

$$\mathbb{E}\sum_{t=1}^{T}\beta^{t-1}\frac{c_t^{1-\gamma}}{1-\gamma} + B\beta^T\frac{a_{T+1}^{1-\gamma}}{1-\gamma}$$

where c_t is consumption, a_{T+1} is terminal wealth (bequest to child), β is the discount factor, and B is the strength of the bequest motive, which captures the degree of altruism. The period utility is CRRA (Constant Relative Risk Aversion), characterized by the inverse of the intertemporal elasticity of substitution (i.e. relative risk aversion) parameter γ.

States. At $t = 1$, the state variables are initial wealth a and pre-college human capital s. Upon labor market entry ($t = 1, m = 0$ or $t = 2, m > 0$), the state variables are wealth a, a $J \times 1$ vector of occupational human capital $h = (h_{m0}, h_{m1}, h_{m2})'$ and major m. Finally, for $t \geq 2, m = 0$ or $t \geq 3, m > 0$, as the individual works in occupation j and does not switch occupation, she only cares about her human capital in occupation j, so the state variables are

(a, h_{mj}, m, j).

Income process. Individual i of age t faces the following income process. While entering the model, she draws a pre-college human capital s from an initial distribution $N(0, \sigma_s^2)$[18]. Upon labor market entry, the individual draws a $J \times 1$ vector of initial occupational human capital. More specifically, h_{imjt} follows:

$$\log h_{imjt} = \log \bar{h}_{mj} + \lambda_j s_i + \eta_{ij,t+1}, \eta_{ij,t+1} \sim N(0, \sigma_{\eta,j}^2) \tag{8}$$

where $\bar{h}_{mj}$ determines the increase in human capital that major m brings to occupation j. λ_j is the return to AFQT. η_{ij} is the idiosyncratic shock on initial occupational talent. $\sigma_{\eta,j}$ captures the standard deviation of the shock, which varies across occupations. Once an occupation is chosen, the working individual receives income subject to occupation-specific idiosyncratic shock and her labor income is subject to progressive taxation specified in (14). Before-tax labor income is comprised of three components:

$$y_{imjt} = \underbrace{w_j}_{\text{occ. efficiency wage}} \quad \underbrace{\Gamma_{jt}}_{\text{life-cycle component}} \quad \underbrace{h_{imjt}}_{\text{occ. human capital}} \tag{9}$$

where w_j is the efficiency wage in occupation j, which is determined in general equilibrium through occupational labor market clearing. Γ_{jt} is the life-cycle component of age t (i.e. earnings profile) in occupation j. h_{imjt} is the idiosyncratic human capital for an individual with major m working in occupation j. h_{imjt} evolves according to an AR(1) process:

$$\log h_{imj,t+1} = \rho_j \log h_{imjt} + \varepsilon_{ij,t+1}, \varepsilon_{ij,t+1} \sim N(0, \sigma_j^2) \tag{10}$$

where ρ_j is persistence, σ_j is the volatility of innovations. Both parameters are occupation-specific and capture earnings risk.

Finally, the individual retires ($t \geq 10$) and receives a fraction π (called the replacement rate) of her pre-retirement income, not subject to taxation, which is given by:

$$y_{imjt} = \pi y_{imj9} \tag{11}$$

As retirement income depends on pre-retirement income, h_{mj} remains a state variable in the retiree's problem. Hence, for $t \geq 10$, we have:

$$h_{imjt} = h_{imj9} \tag{12}$$

[18] It is certainly possible that students from different parental income groups are differentially prepared in terms of their cognitive skills: richer students are more likely to be better prepared. Figure A.2 in Appendix A.4 plots the distribution of normalized AFQT scores by parental income quartiles. Although given the entire sample, the distribution of AFQT shifts more to the right the higher parental income quartile gets (Panel (a)), the distribution almost overlap across quartile groups if the sample is restricted only to college enrollees (Panel (b)). As the focus of the paper is mainly on the intensive margin, this assumption may be less worrisome than it seems.

Technology. There is a representative firm producing final good. Final goods Y are produced following a Cobb-Douglas production technology $Y = F(K, L) = \bar{A}K^{\alpha}L^{1-\alpha}$, where $\bar{A}$ denotes productivity, K is capital, L is composite labor and α is the capital share. The composite labor is a CES aggregator over J occupations given by:

$$L = \Big(\sum_{j=1}^{J} Z_j L_j^{\frac{\chi-1}{\chi}} \Big)^{\frac{\chi}{\chi-1}} \tag{13}$$

where Z_j and L_j denote the productivity and total efficiency units in occupation j, χ is the elasticity of substitution between the J occupations.

Government. The government issues college subsidies and retirement income. It collects labor taxes from working individuals following a progressive tax schedule. After-tax labor income follows the specification similar to Heathcote, Storesletten and Violante (2017):

$$y - T(y) = (1 - \tau_0)y^{1-\tau_1} \tag{14}$$

where y is the pre-tax labor income, $T(y)$ is the amount of tax, τ_0 is the average tax rate (level of taxation) and $\tau_1 \in [0, 1]$ is the level of progressivity. Tax progressivity increases with τ_1, and $\tau_1 = 0$ implies a linear tax (flat tax) schedule. τ_0 adjusts to satisfy government budget balance in all counterfactuals.

4.2 Recursive formulation and decision rules

For expositional simplicity, I remove the time subscripts if possible.

$\boldsymbol{t = 1:}$

The value function of an individual with states (a, s) is:

$$V_t(a, s) = \max_{m=0,1,2} \{\mathbb{E}V_t^{m=0}(a, s, \nu_{m=0}), \max_{m=1,2} \{V_t^m(a, s) + \xi_m\}\}$$

The individual makes a discrete choice of major $m = 0, 1, 2$ that gives her the highest value. $\mathbb{E}V_t^{m=0}(a, s, \nu_{m=0})$ is the expected value of not attending college ($m = 0$). The expectation is taken over two sources of idiosyncratic uncertainty: the initial draw of occupational human capital and occupational taste shock $\nu_{m=0}$. The value of $m = 1$ or $m = 2$ is comprised of $V_t^m(a, s)$ and a non-pecuniary component ξ_m, an idiosyncratic major-specific taste shock.

If the individual decides to forgo college ($m = 0$), she makes an occupational (career) choice and starts working. Her value function of working is:

$$
\begin{aligned}
V_t^m(a, h_{m0}, h_{m1}, h_{m2}, \nu_m) &= \max_{j=0,1,2}\{V_t^{m,j}(a, h_{m0}, h_{m1}, h_{m2}) + \nu_m\} \\
V_t^{m,j}(a, h_{m0}, h_{m1}, h_{m2}) &= \max_{c,a'} u(c) + \beta \mathbb{E} V_{t+1}(a', h'_{mj}, m, j) \\
c + a' &= (1+r)a + (y_{mj} - T(y_{mj})) \\
a' &\geq \underline{a}_m
\end{aligned} \tag{15}
$$

where $V_t^{m,j}$ is the value of working in occupation j for major m worker. ν_m is drawn from a Type I Extreme Value distribution with scale parameter ψ_m, which captures the dispersion of taste shock. I allow ψ_m to vary across majors to account for the possibility that preference may be more correlated across time for certain majors. Following McFadden (1973), Type I Extreme Value assumption on occupational taste shock implies a closed-form solution to occupational choice probabilities. The probability of choosing occupation j for major m worker is:

$$
\Pr(j|a, h_{m0}, h_{m1}, h_{m2}, m) = \frac{\exp\left(\frac{V_t^{m,j}(a,h_{m0},h_{m1},h_{m2})}{\psi_m}\right)}{\sum_{j=0,1,2}\exp\left(\frac{V_t^{m,j}(a,h_{m0},h_{m1},h_{m2})}{\psi_m}\right)} \tag{16}
$$

The problem is similar for $t = 2, m > 0$.

If the individual decides to attend college ($m > 0$), she chooses the major $m = 1, 2$ that yields the highest value. The value of choosing major m is:

$$
\begin{aligned}
V_t^m(a, s) &= \max_{c,a'} u(c) + \beta \mathbb{E} V_{t+1}^m(\tilde{a}(a'), h'_{m0}, h'_{m1}, h'_{m2}, \nu_m) \\
c + a' &= (1+r)a - (1 - g_m \mathbb{1}(a <= a_{p25}))P_e \\
a' &\geq \underline{a}_m
\end{aligned} \tag{17}
$$

where $\tilde{a}(a')$ is a function that transforms student debt $b = -a', a' < 0$ incurred at $t = 1$ into risk-free bonds. This transformation allows me to reduce student debt as an extra state variable and hence reduce computational burden[19]. Appendix B.1 provides a detailed derivation of $\tilde{a}(a')$.

Finally, I assume that the major taste shock also follows a Type I Extreme Value distribution with location parameter κ_m and scale parameter θ. The former captures the non-pecuniary value of the major, valued by everybody. A negative κ_m implies that major m brings disutility. As discussed in Section 5.2, allowing for the possibility of non-zero κ_m is essential to match the overall major share as observed in the data. Exploiting the properties of Type I Extreme Value distribution, the probability of choosing major m is:

$$
\Pr(m|a, s) = \frac{\exp\left(\frac{V_t^m(a,s)+\kappa_m}{\theta}\right)}{\sum_{m=0,1,2}\exp\left(\frac{V_t^m(a,s)+\kappa_m}{\theta}\right)} \tag{18}
$$

[19] This transformation is also used in Abbott et al. (2019) and Daruich (2022).

$\boldsymbol{t = 2 - 9, m = 0;\ t = 3 - 9, m > 0:}$

$$\begin{aligned} V_t(a, h_{mj}, m, j) &= \max_{c,a'} u(c) + \beta \mathbb{E} V_{t+1}(a', h'_{mj}, m, j) \\ c + a' &= (1+r)a + (y_{mj} - T(y_{mj})) \\ a' &\geq \underline{a}_m \end{aligned} \tag{19}$$

$\boldsymbol{t = 10 - 11:}$

$$\begin{aligned} V_t(a, h_{mj}, m, j) &= \max_{c,a'} u(c) + \beta V_{t+1}(a', h'_{mj}, m, j) \\ c + a' &= (1+r)a + y_{mj} \\ a' &\geq 0 \end{aligned} \tag{20}$$

$\boldsymbol{t = 12:}$

$$\begin{aligned} V_t(a, h_{mj}, m, j) &= \max_{c,a'} u(c) + B\beta \frac{a'^{1-\gamma}}{1-\gamma} \\ c + a' &= (1+r)a + y_{mj} \\ a' &\geq 0 \end{aligned} \tag{21}$$

4.3 Stationary equilibrium

Let $s_t \in S_t$ be the state vector of an individual of age t. A stationary recursive competitive equilibrium consists of (i) prices $\{w_0, w_1, w_2, r\}$ and average tax rate τ_0, (ii) individual policy functions $\{c_t(s_t), a_{t+1}(s_t), m(s_t), j(s_t)\}$, (iii) value functions $\{V_t(s_t)\}$, (iv) aggregate capital and occupational labor inputs $\{K, L_0, L_1, L_2\}$, (v) a vector of measures μ such that:

1. Given prices, the policy functions solve the individual's problem and $\{V_t(s_t)\}$ is the associated value functions.

2. Given prices, aggregate capital and occupational labor inputs solve the firm's problem.

3. Labor market clears for each occupation $j = 0, 1, 2$:

$$L_j = \sum_{t=1}^{9} \int_{S_t} \mathbb{1}((s_t) = j) \exp(\Gamma_{jt} h_{mjt}(s_t)) d\mu_t \tag{22}$$

4. Asset market clears:

$$K = \sum_{t=1}^{T} \int_{S_t} a_t(s_t) d\mu_t \tag{23}$$

5. Goods market clears:

$$\sum_{t=1}^{T}\int_{S_t} c_t(s_t)d\mu_t + \int_{S_1}\mathbb{1}(m(s_1)\geq 1)P_e d\mu_1 + G + \delta K = F(K,L) \tag{24}$$

where G is exogenous government spending.

6. Government budget balance:

$$\int_{S_1} g_m P_e \mathbb{1}(m(s_1)\geq 1)\mathbb{1}(a\leq a_{p25})d\mu_1 + G + \pi\sum_{t=10}^{T}\int_{S_t} y_9(s_9)d\mu_t = \sum_{t=1}^{9}\int_{S_t} T(y_t(s_t))d\mu_t \tag{25}$$

7. Individual and aggregate behaviors are consistent. Measures μ is a fixed point of $\mu(S) = Q(S,\mu)$, where $Q(S,\cdot)$ is the transition function generated by policy functions and exogenous laws of motion, S is the generic subset of the Borel-sigma algebra defined over the state space.

Details on the computational algorithm can be found in Appendix B.2.

5 Parameterization

This section provides details on model parameterization. The model is calibrated to the U.S. economy in three steps. First, I externally assign some parameters to their standard values. I then calibrate the income process. Lastly, the remaining parameters are chosen in order to minimize the distance between a number of moments in the model and in the data.

5.1 Externally assigned parameters

The assigned parameters are reported in Table 4. I set the coefficient of relative risk aversion γ to 2, which corresponds to an intertemporal elasticity of substitution of $1/2 = 0.5$, a standard value in the literature. $g_m = 0.25$, which reflects the current state of Pell grant in the U.S.. The annual interest rate spread on student loans ι_b (relative to the risk-free rate) equals to 0.03, a very conservative value[20]. I choose $\tau_0 = 0.2$ to match the average income tax rate from the CBO, and tax progressivity $\tau_1 = 0.23$ is taken from Heathcote, Storesletten and Violante (2017). I assign the retirement replacement ratio π and annual depreciation rate of capital to common values of 0.8 and 0.025, respectively. I allow the exogenous borrowing limit to be more relaxed for college workers ($m > 0$) compared to non-college workers ($m = 0$). The composite labor production function is assumed to be Cobb-Douglas ($\chi = 1$). One implication of Cobb-Douglas production function is that occupational productivity Z_j equals the factor share of occupation j, hence Z_j can be directly computed from the ACS/CPS[21].

[20] See https://educationdata.org/average-student-loan-interest-rate.

[21] Both the ACS and CPS yield similar values.

Parameter	Description	Value	Source
γ	1/IES	2	standard
g_m	college subsidy rate	0.25	Pell grant
ι_b	annual student loan spread	0.03	standard
τ_0	level of tax rate	0.2	CBO (2013)
τ_1	tax progressivity	0.23	Heathcote et al. (2017)
π	replacement ratio	0.80	standard
$\underline{a}_m$	borrowing limit	[0 -1]	standard
δ	capital depreciation rate	$1-(1-0.025)^5$	standard
χ	elasticity of substitution btw. occ.	1	Cobb-Douglas
Z_j	occupational productivity	[0.36, 0.25, 0.39]	ACS, CPS

Table 4: Externally Assigned Parameters

Notes: For the value of Z_j, the first element of the vector is for occupation 0, the second element is for occupation 1, the third element is for occupation 2.

5.2 Calibrated parameters

Income process. I follow two steps to estimate the income process, occupation by occupation. In the first step, I directly estimate earnings regressions to obtain three sets of occupation-specific parameters: the life-cycle component Γ_j (see Figure 7 in Section 3.4 and Table B.1 in Appendix B.3), return to AFQT λ_j (B.2 in Appendix B.3) and more importantly, $\log \bar{h}_{mj}$ (Table 5). Table 5 shows that major 1 (e.g.: STEM, Health, majors chosen by poorer students) is the major that best prepares students to occupation 1 (e.g.: architecture/engineer, healthcare practitioner), whereas major 2 (e.g.: Business, Social Science, majors chosen by richer students) is the major that best prepares students to occupation 2 (e.g.: management, sales), consistent with intuition[22].

In the second step, I use the minimum distance estimator to pin down $\rho_j, \sigma_{\eta,j}$, and σ_j. I do so by matching the variances of log residual earnings of different age groups, one-lagged auto-covariance of log residual earnings, and the standard deviation of log residual earnings growth. Table 6 shows that the calibrated parameters for $\sigma_{\eta,j}$ and σ_j are indeed lower for occupation 1 than occupation 2. Lower values of $\sigma_{\eta,1}$ and σ_1 imply lower earnings risk in the typical occupation for major 1, the major group that poorer students tend to choose. Table 7 reports

[22] Using the methodology described in Appendix A.7, I compute my baseline measure for major specificity: the standard deviation of de-meaned $\log \bar{h}_{mj}$ across occupations. The value for major 1 is 0.07, compared to 0.04 for major 2, implying that major 1 is more specific than major 2. This is consistent with the empirical finding that majors taken by poorer students are more specific (Appendix A.7).

the moments used in the calibration and their model counterparts. Appendix B.3 contains a more detailed description of the estimation procedure for the income process.

	Occ. 0	Occ. 1	Occ. 2
Major 0	0	0	0
Major 1	0.165	0.379	0.232
	(0.024)	(0.018)	(0.021)
Major 2	0.144	0.212	0.252
	(0.015)	(0.019)	(0.012)

Table 5: Estimates of $\log \bar{h}_{mj}$

Notes: Robust standard errors are in parentheses.

Parameter	Description	Value
$\sigma_{\eta,j}$	st. dev. initial occ. talent shock	[0.53, 0.45, 0.51]
ρ_j	persistence income shock	[0.95, 0.95, 0.94]
σ_j	st. dev. income shock	[0.35, 0.30, 0.34]

Table 6: Income Process Parameters

Notes: For the value column, the first element of the vector is for occupation 0, the second element is for occupation 1, the third element is for occupation 2.

Moment	Data	Model
variance of log earnings, age 20-25	[0.35, 0.27, 0.31]	[0.31, 0.23, 0.30]
variance of log earnings, age 25-39	[0.50, 0.36, 0.47]	[0.50, 0.36, 0.48]
autocovariance of log earnings, one lag	[0.40, 0.38, 0.41]	[0.40, 0.38, 0.40]
st. dev. of log earnings growth	[0.63, 0.52, 0.59]	[0.36, 0.30, 0.34]

Table 7: Income Process Parameters: Model vs. Data

Notes: For the data and model columns, the first element of the vector is for occupation 0, the second element is for occupation 1, the third element is for occupation 2.

SMM. I use Simulate Method of Moments (SMM) to jointly determine the remaining parameters. Table 8 presents the parameter values that achieve the best fit. Table 9 reports the targeted moments and their model counterparts. The discount factor β is calibrated to match the long-run risk-free interest rate of 0.04, as in Lee and Seshadri (2019). The bequest-to-wealth ratio 0.003 (Gale and Scholz (1994)) is informative of the altruism parameter B. The relevant moments for non-pecuniary values of major 1 and 2 (κ_1, κ_2) are the share in major 1 conditional on college and the (unconditional) college share. The scale parameter of the major taste shock θ, which captures the dispersion of the taste shock, is chosen to match the ratio of unconditional variance of log earnings to variance of log earnings conditional on major[23]. The college cost P_e is related to the share of workers in occupation 0. Finally, the major-specific scale parameter of the occupational taste shock ψ_m are pinned down by the typical occupation's share in each major (Table 1) as well as the variance of log earnings conditional on major. Exogenous government spending G and productivity of the final good $\bar{A}$ are chosen to ensure government budget balance and $w_0 = 1$ (a normalization) in the baseline steady state.

Parameter	Description	Value
β	discount factor	0.94
B	altruism	9.82
κ_1	location parameter, major 1	-0.11
κ_2	location parameter, major 2	0.06
θ	scale parameter, major taste	0.30
P_e	college cost	0.85
ψ_m	scale parameter, occupational taste	[0.04, 0.05, 0.01]

Table 8: Calibrated Parameters

Notes: For the value of ψ_m, the first element of the vector is for occupation 0, the second element is for occupation 1, the third element is for occupation 2.

Moment	Data	Model
risk-free interest rate	0.04	0.04
bequest/wealth ratio	0.003	0.009
share in major 1 conditional on college	0.39	0.40
college share	0.35	0.36
unconditional var./var. conditional on major	1.045	1.040
share of workers in occupation 0	0.43	0.40
variance of log earnings conditional on major	0.485	0.378
typical occupation's share by major	[1.15, 1.71, 1.61]	[1.15, 1.71, 1.36]

Table 9: Calibrated Parameters: Model vs. Data

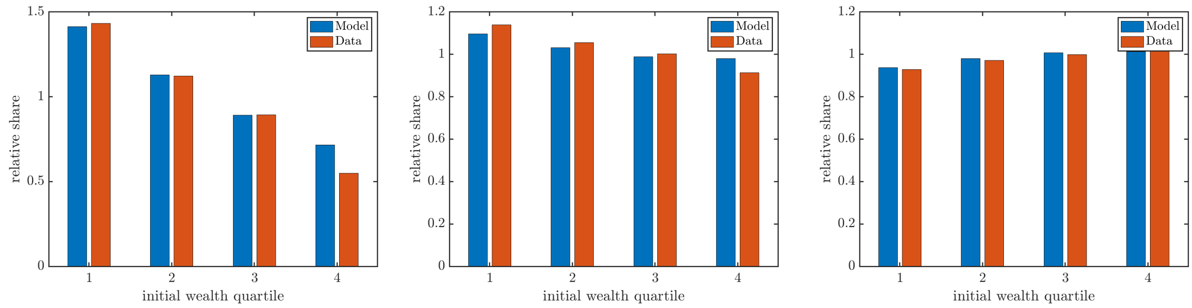
Notes: For the data and model of typical occupation's share by major, the first element of the vector is for occupation 0, the second element is for occupation 1, the third element is for occupation 2.

[23] This is the variance of log earnings net of major fixed effects ($\log \bar{h}_{mj}$).

5.3 Model fit

I conduct two exercises to assess the model's ability to account for additional features of the data that are not directly targeted in the calibration. First, I test whether the model reproduces the sorting patterns by initial wealth as in the data. Second, I evaluate its implications on income inequality.

Major choice by initial wealth. One of the key points of this paper is that students from different levels of initial wealth sort into different types of majors. Therefore, I evaluate whether the model is able to replicate the relative major shares by initial wealth quartiles in Table 2. Figure 9 shows that the model indeed reproduces the sorting patterns in the data, as the blue (model) and red (data) bars align closely.



(a) no college (b) major 1 (c) major 2

Figure 9: Major Choice by Initial Wealth Quartiles

Notes: Data moments (red bars) are computed in Table 2. Model moments (blue bars) are computed from the stationary distribution μ. Relative major share (y-axis), as defined in equation (7) in Section 3.4. Initial wealth quartile is on the x-axis. Panel (a) is the relative non-college share, defined as the share of non-college individuals in the initial wealth quartile, adjusted for the overall non-college share. Panel (b) is the relative share of major 1 conditional on college. It is defined as the share of major 1 conditional on college for the initial wealth quartile, adjusted for the overall share of major 1 conditional on college. Panel (c) is the share of major 2 conditional on college.

Untargeted moments: income inequality. Table 10 reports the model and empirical moments on income inequality (measured as differences in p90-10, p90-50 and p50-10 in log labor earnings). The baseline measure is computed by taking the average of these statistics for the years 2000-2019 from the Current Population Survey (CPS). The median wealth to median income ratio is taken from Kuhn and Ríos-Rull (2016). The model is able to fit these untargeted moments well.

Moment	Data	Model	Source
income inequality, p90-10	5.41	5.36	CPS
income inequality, p90-50	2.45	2.45	CPS
income inequality, p50-10	2.21	2.19	CPS
median wealth/median income	2.13	1.51	Kuhn and Ríos-Rull (2016)

Table 10: Untargeted Moments: Income, Wealth

6 Results

I now use the model to (*i*) quantify the three determinants (i.e.: earnings profile, earnings risk, non-pecuniary value of majors) for sorting, (*ii*) study the sorting patterns, as well as the aggregate and distributional consequences of college subsidies, unconditional or conditional on majors.

6.1 Quantify the importance of the determinants for sorting

The model incorporates the three potential determinants for sorting: earnings profile (Γ_j), earnings risk ($\sigma_{\eta,j}, \sigma_j$) and non-pecuniary value of majors (κ_m).

Before presenting the methodology and quantitative results, I discuss how these three determinants are related to sorting by initial wealth. Under incomplete markets, where individuals face borrowing constraints and uninsurable idiosyncratic risk, lower wealth individuals may choose majors with a flatter earnings profile. They prefer front-loading their labor earnings either because (*i*) they are directly liquidity constrained by the time they graduate, or (*ii*) higher initial earnings allow them to better build up their buffer stock of savings. This second reason also applies to why lower wealth individuals prefer lower earnings risk majors. Finally, lower wealth individuals are more likely to forgo the non-pecuniary value of majors for higher earnings. This mechanism is at play as long as the value function is concave, as the marginal value of one extra dollar decreases in wealth.

Quantify the three determinants. I quantify the three determinants by shutting down each element one-by-one and compute the new steady state in general equilibrium. More specifically, I set each element to their average value (weighted by the occupational or major share). The baseline is considered to be the scenario in which all three elements are at play. I examine the change in relative share in major 1 for the bottom quartile in each experiment relative to the baseline.

Panel (a) of Table 11 presents the results. Each row is the element that is shut down (set to the average value). Column 1 is the relative share of major 1 for the lowest initial wealth quartile, as defined by (7). I define the degree of sorting by the relative major share (Column 1) minus 1, i.e. the percentage deviation from overall major share. Column 2 is the percentage change of the degree of sorting in the counterfactual relative to the baseline.

Panel (a) of Table 11 highlights the quantitative importance of earnings risk in driving poorer students' major choice. If the earnings profile of occupation 1 was steeper and the one of occupation 2 was flatter, even more poorer students would choose major 1. The low earnings growth prospect of major 1 actually disincentivizes poorer students from choosing major 1. If both $\sigma_{\eta,j}$ and σ_j were higher in occupation 1, less poorer students would choose major 1. The degree of sorting in major 1 falls by 50%. Finally, making both majors having the average non-pecuniary value would lower the relative major share of the bottom quartile in major 1. This is because as major-specific non-pecuniary values are set to the average value, major 1 has higher non-pecuniary value and major 2 has lower non-pecuniary value. As a result, the overall share of major 1 increases for all students, from 0.40 to 0.54. To summarize, these experiments suggest that low earnings risk in occupation 1, the most likely occupation of major 1, is the main force for why poorer students sort into major 1.

Additional results on earnings risk. Given the importance of earnings risk, I further analyze this component by performing two additional sets of experiments. Panel (b) of Table 11 shows the results. First, I separately shut down $\sigma_{\eta,j}$ and σ_j to explore the importance of initial occupational talent uncertainty vs. life-cycle income uncertainty. The quantitative importance of both types of uncertainty is similar. As $\sigma_{\eta,j}$ is immediately resolved at the time of occupational choice and σ_j is only resolved until retirement, this result highlights the importance of initial occupational talent uncertainty. Second, I increase the relative risk aversion parameter γ to 4. As individuals become more risk-averse, the non-college share increases from 0.65 to 0.73, and poorer students sort into the lower earnings risk major even more.

The role of $\bar{h}_{mj}$. I investigate the role of specific human capital of majors m for occupation j, namely $\bar{h}_{mj}$. I conduct three experiments: (i) set $\log \bar{h}_{11}$ to the average value of $\log \bar{h}_{m1}$ across majors, (ii) set $\bar{h}_{22}$ to the average value of $\log \bar{h}_{m2}$ across majors, and (iii) set both $\log \bar{h}_{11}$ and $\log \bar{h}_{22}$ to their average values of across majors. Panel (c) of Table 11 suggests that the specificity of major 1 for occupation 1 (manifested by the very high $\bar{h}_{11}$) is an important contributing factor for poorer students' sorting into major 1. If $\bar{h}_{11}$ were smaller, significantly less number of poorer students would choose major 1.

	relative share major 1, quartile 1	% change sorting relative to baseline
Panel (a):		
baseline	1.12	0
earnings profile	1.13	8.33
earnings risk (both)	1.06	-50
non-pecuniary value	1.08	-33.33
Panel (b):		
$\sigma_{\eta,j}$ only	1.10	-16.67
σ_j only	1.09	-25
$\gamma = 4$	1.22	83.33
Panel (c):		
$\bar{h}_{11}$ only	1.04	-66.67
$\bar{h}_{22}$ only	1.12	0
both $\bar{h}_{11}$ and $\bar{h}_{22}$	1.04	-66.67

Table 11: Quantitative Importance of Determinants for Sorting

Notes: Each row is the element that is shut down (set to the average value). Column 1 is the relative share of major 1 for the lowest initial wealth quartile, as defined by (7). Define the degree of sorting by the relative major share (Column 1) minus 1, i.e. the percentage deviation from overall major share. Column 2 is the percentage change of the degree of sorting in the counterfactual relative to the baseline. Panel (a) reports the results for quantifying the three channels. Panel (b) reports additional results on earnings risk. Panel (c) reports the results for investigating the role of specific human capital $\bar{h}_{mj}$.

6.2 Macroeconomic implications of college subsidies

Next, I study the aggregate and distributional implications of college subsidies: unconditional or conditional on major. In this section, I consider college subsidies distributed only to individuals from the bottom quartile of the initial wealth distribution. This configuration is more in line with Pell grant in the U.S., which targets low-income students. Moreover, by only allowing college subsidies to be distributed to the bottom quartile is a more meaningful comparison. As poorer students are more likely to choose major 1, it is difficult to disentangle this composition effect from the impact of college subsidy per se, if the college subsidy is given to all (i.e. universal college subsidy). In this sense, a universal college subsidy acts as a targeted transfer to poorer students due to the composition effect. In Section 7.2, I present results for universal college subsidies. Universal college subsidies can be conceptualized as tuition policies.

A conditional subsidy on major in this situation is similar as differential tuition pricing by major.

Major choice by initial wealth quartiles. Before examining the macroeconomic implications, I explore major choices by initial wealth quartiles under different college subsidy regimes. I show that expansion in unconditional college subsidies is not sufficient to induce poorer students to switch into majors originally chosen by richer students. Figure 10 suggests that only very few students from the bottom quartile switch from major 1 to major 2 under unconditional college subsidies. Most students remain in the majors they used to choose before the expansion. This result is contrary to the intuitive view that college financing policies alleviate poorer students' financial burden, thereby inducing them to choose majors currently taken by the rich. Some research supports this view for income-based student debt repayment schemes (Murto (2022), Alon et al. (2022)). However, my policy experiments suggest that for college subsidies, this is not the case.

Intuitively, a college subsidy has two roles. First, it directly reduces the college cost. This is a pure income effect and applies to all forms of college subsidies, unconditional or conditional. Conditional subsidy has an additional role. It changes the relative prices between major 1 and major 2, thereby affecting the expected value of each major. This effect can be viewed as a substitution effect. My finding suggests that the pure income effect of college subsidies is not sufficient for poorer students to sacrifice earnings risk for higher non-pecuniary value majors and "pursue their dreams". Lower earnings risk is indeed a very important consideration for low-wealth individuals.

Aggregate implications. I now study the aggregate and distributional implications of college subsidies in steady states, unconditional or conditional on majors. First, I show how key macro aggregates (occupational efficiency wages w_j, risk-free interest rate r, average tax rate τ_0, college share) evolve as college subsidy rate g_m increases.

I then move on to compute the average welfare gains across policies and how welfare gains are distributed by initial wealth quartiles. Note that directly comparing the outcome variables at a given subsidy rate under different regimes is not meaningful. This is because given the same rate, the total subsidies spent are not equalized across policy regimes. At a given rate, an unconditional subsidy implies a higher amount of total subsidies spent than a conditional subsidy. Therefore, when making welfare comparisons across different types of college subsidies later on, I hold the total subsidies spent constant across experiments and search for the g_m's that satisfy this criteria. Table B.5 in Appendix B.5 provides details on key variables under the three subsidies schemes.

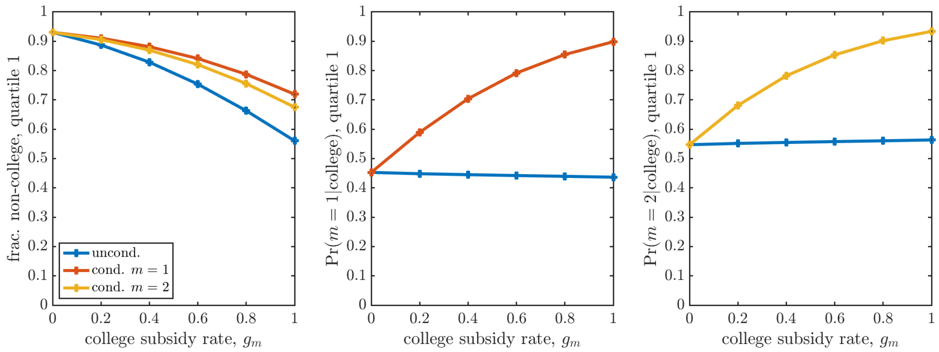


Figure 10: Major Choice of the Bottom Quartile, Initial Wealth

Notes: Each line plots the major choice probabilities for the bottom quartile of the initial wealth steady state distribution. The blue line is under unconditional college subsidies, $g_1 = g_2$. The red line is under college subsidies conditional on major 1, $g_2 = 0$. The yellow line is under college subsidies conditional on major 2, $g_1 = 0$. x-axis is the level of college subsidy rate g_m. All are steady-state comparisons. The left panel is the non-college share. The middle panel is the share of major 1 conditional on college. The right panel is the share of major 2 conditional on college.

Figure 11 depicts changes in the steady-state values of various macro aggregates at different levels of college subsidy rate g_m. The blue line is under unconditional college subsidies, where $g_1 = g_2$. The red line is under college subsidies conditional on major 1, where $g_2 = 0$. The yellow line is under college subsidies conditional on major 2, where $g_1 = 0$.

As the college subsidy rate increases, lower share of individuals forgo college, efficiency wage in occupation 0 (w_0) thus increases. Whether w_1 and w_2 rise or fall depend on the type of subsidies. If the college subsidy is conditional on major 1 (i.e.: major chosen by poorer students), higher share of students choose major 1, labor supply in occupation 1 rises, w_1 falls and w_2 rises. The same logic applies to college subsidies conditional on major 2. However, the fall in w_1 under conditional subsidy on major 1 is stronger than the fall in w_2 under conditional subsidy on major 2. This is because major 1 is more specific than major 2. Therefore, higher share of graduates from major 1 sort into its typical occupation (occupation 1), whereas higher share of graduates from major 2 are more evenly sorted across occupations.

The equilibrium interest rate decreases with college subsidy rate, as saving is higher. This fall in equilibrium risk-free interest rate also reduces the student loan rate. As more workers are now college-educated, human capital and the total tax base (for a given tax rate τ_0) in the economy increase by more than the increase in total spending on college subsidies, thereby reducing the average tax rate τ_0 that balances the government budget.

I now turn to examine welfare, I use the consumption equivalent value (CEV) as my measure of welfare gains from policies. CEV is defined as the percentage increase in consumption needed to make the agent indifferent between the new equilibrium and the baseline steady state. I compute the average welfare by integrating individual welfare gains over the baseline initial steady state distribution.

To ensure comparability across policies, the values of g_m in each experiment should satisfy two criteria: (i) college subsidies are only given to the bottom quartile students in the initial wealth distribution[24], (ii) total subsidies spent are equalized across experiments. Hence, I compare three college subsidies policies. First, I set $g_1 = g_2 = 0.70$, which is the fraction of college cost that Pell grant used to cover in the 1980s. I then search for the conditional subsidy rates that satisfy criteria (ii) in equilibrium. The corresponding values for g_m are such that $g_1 = 0.92$ and $g_2 = 0$ for subsidies conditional on major 1, and $g_1 = 0$ and $g_2 = 0.84$ for subsidies conditional on major 2. The subsidy rate is smaller if it is conditional on major 2 than major 1. This is because major 2 is inherently higher non-pecuniary value, so more students will choose major 2, all else equal. Hence, in order to keep the total subsidies spent equalized across experiments, the subsidy rate has to be smaller.

I find that conditional subsidies on major 1 (i.e. the major that poorer students tend to choose in baseline) yields the highest average welfare (0.94 percent), compared to unconditional subsidies (0.83 percent) or conditional subsidies on major 2 (0.64 percent). In the next (sub)section, I explore how welfare is distributed across initial wealth groups to better understand why conditional subsidies on major 1 dominate.

Distributional implications. I evaluate how the welfare gains are distributed across the initial wealth distribution under various policies. I show that the bottom quartile achieves substantial welfare gains at the expense of the other three quartiles. In Figure 12, each bar represents the steady-state average welfare gain (measured as the percentage change in CEV relative to the baseline) by initial wealth quartile. The initial wealth quartile is derived from the baseline steady state distribution. For the bottom quartile, conditional subsidies on major 1 lead to the highest average welfare gains (4.50 percent), compared to unconditional subsidies (3.83 percent) or conditional subsidies on major 2 (3.26 percent). The large welfare impact on the bottom quartile drives the aggregate result in the previous (sub)section. The top three quartiles incur welfare losses due to lower equilibrium occupational wages in occupation 1 and/or 2 (the most

[24] Although CEV is computed for individuals from the baseline steady state distribution, a_{p25} is derived from the new steady state equilibrium.

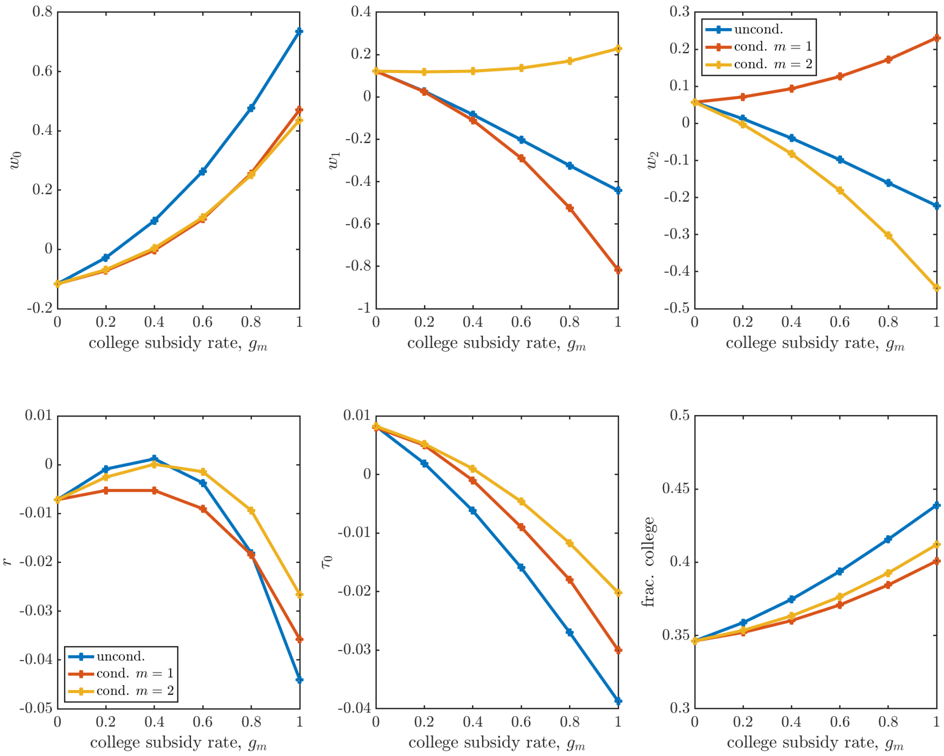


Figure 11: Aggregate Implications of College Subsidies

Notes: The blue line is under unconditional college subsidies, $g_1 = g_2$. The red line is under college subsidies conditional on major 1, $g_2 = 0$. The yellow line is under college subsidies conditional on major 2, $g_1 = 0$. x-axis is the level of college subsidy rate g_m. All are steady-state comparisons. w_0, w_1, w_2 (left, middle, right panels at the top) are expressed as percentage changes relative to the baseline ($g_m = 0.25$, blue line). r and τ_0 (left and middle panels at the bottom) are expressed as level changes relative to the baseline. Fraction of college (i.e. college share at $t = 1$, right bottom panel) is expressed in level.

associated occupations for major 1 and major 2) and interest rate. The welfare loss is partially compensated by the reduction in average tax rate.

Why do conditional subsidies on major 1 dominate (to the bottom quartile and in the aggregate)? Intuitively, there are several channels through which inefficiency may arise. First, it could be that students are directly liquidity constrained and loosening financial constraint makes them attend college. Second, uninsurable income uncertainty makes college a risky decision, leading to underinvestment in college education. Making major 1 (the lower earnings risk major) relatively cheaper incentivizes students to attend college. Third, as college share is higher, and major 1 develops more human capital for occupation 1 and 3 compared to major 2, the tax base is larger, thereby reducing the average tax rate that is needed to balance the government budget.

I find that the third channel is the most relevant. First, conditional subsidies on major 1 lead to 4 percentage points lower fraction of college attendees from the bottom quartile compared to unconditional subsidies. However, the fraction of students from the bottom quartile who choose major 1 is 9 percentage points higher under conditional subsidies on major 1 than unconditional subsidies. Given the importance of low earnings risk of majors for low-wealth individuals under incomplete markets, conditional subsidies on major 1 encourage poorer students to choose major 1. These students receive a higher rate of subsidy, as the subsidy is now only given to students in major 1[25]. Students in major 2 or those who would have chosen to attend college under unconditional subsidies but no longer choose to attend under conditional subsidies on major 1 now have lower welfare gains. The positive effect for major 1 students dominates, so average welfare is higher. Second, average tax rate τ_0 falls by the most for conditional subsidies on major 2. Having more graduates from major 1 increases the tax base of the economy, thereby reducing the average tax rate. This general equilibrium effect on τ_0 acts as an externality and increases welfare for all.

Taking stock. My quantitative results highlight the importance of low earnings risk for low wealth individuals under incomplete markets. There are four main takeaways. First, earnings risk is the most quantitatively important determinant of poorer students' major choice. Second, expansion in (unconditional) college subsidies is not sufficient to induce poorer students to switch into majors originally chosen by richer students. Third, keeping the total subsidies spent equalized across experiments, conditional subsidies on majors currently chosen by poorer students generate the highest average welfare gains than either unconditional subsidies or conditional subsidies on majors currently chosen by richer students. Fourth, welfare gains are not evenly distributed across initial wealth groups. Individuals at the bottom quartile of the initial wealth distribution achieve substantial welfare gains, at the expense of the other three quartiles.

7 Robustness and Extensions

In this section, I discuss two possible robustness/extensions.

7.1 Testing preference heterogeneity

There are alternative mechanisms through which parental income could affect students' choices. First, it is possible that richer and poorer students exhibit preference heterogeneity. Second, there may be intergenerational transmission of tastes on majors. To address the first concern, in my context, one need to test whether students from different parental income groups have similar levels of patience (for earnings profile) or risk aversion (for earnings risk). This test can

[25] 22% of individuals from the bottom quartile receive college subsidies under conditional subsidies on major 1, compared to 29% under unconditional subsidies and 24% under conditional subsidies on major 2.

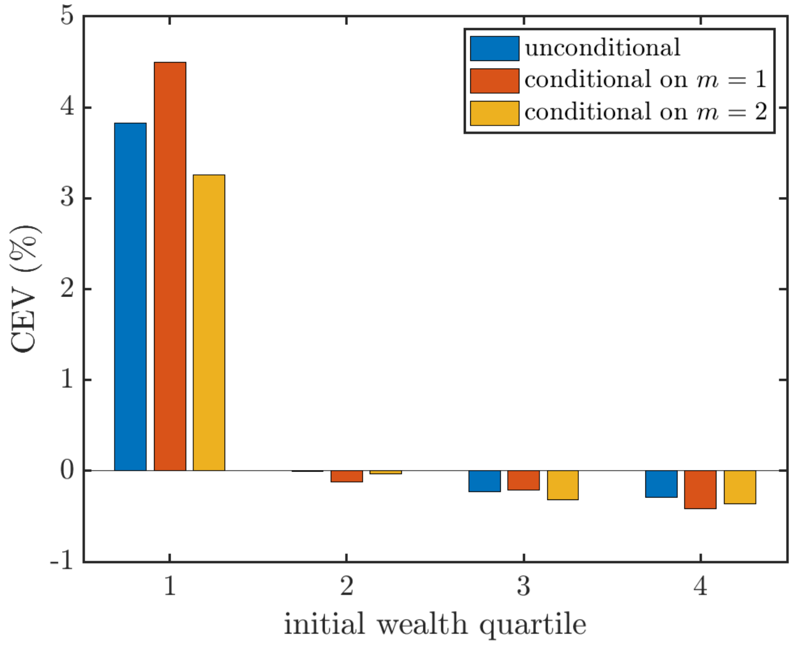


Figure 12: Average Welfare Gains by Initial Wealth Quartile

Notes: Each bar represents the steady-state average welfare gain (measured as the percentage change in certainty equivalent value (CEV) relative to the baseline, where $g_1 = g_2 = 0.25$) in the initial wealth quartile. CEV is defined as the percentage increase in consumption needed to leave the agent indifferent between the new policy and the baseline. The blue bar is under unconditional college subsidies ($g_1 = g_2 = 0.7$). The red bar is under college subsidies conditional on major 1 ($g_1 = 0.92, g_2 = 0$). The yellow bar is under college subsidies conditional on major 2 ($g_1 = 0, g_2 = 0.84$). x-axis is the initial wealth quartile. Initial wealth quartile is derived from the baseline steady-state distribution.

be conducted in my quantitative model by assigning students from below the 25 percentile (or median) of the initial wealth distribution a higher discount factor β or lower relative risk aversion σ[26] than the above 25 percentile (or median) group and examine whether poorer students' major choices are sensitive to the change. To address the second concern, one would ideally need information on parent's major choice and control for this variable in the multinomial logit regression. However, such information is typically not available. One could test this with information at the occupational level for college educated parents and children.

7.2 Tuition pricing policies

Given the growing practices of differential tuition pricing by major, I conduct experiments on colleges subsidies to all students (i.e. not only to the individuals at the bottom quartile of the initial wealth distribution). Conceptually, a universal college subsidy is equivalent to a tuition

[26]Poorer students front-load their labor earnings because they are more impatient, or choose lower earnings risk majors because they are more risk averse.

pricing policy. Free tuition is equivalent to $g_m = 1$ to all students, and differential pricing on major is equivalent to a conditional subsidy on major to all students. Section B.6 reports the results. In a nutshell, college subsidies to all increase the college share, aggregate output and inequality by more than subsidies distributed to the bottom quartile only. However, average tax rate τ_0 is higher than the baseline under universal subsidies across all three experiments. Moreover, richer students are now more responsive compared to the bottom-quartile only subsidies.

8 Conclusion

In light of the U.S. higher education affordability crisis, this paper rethinks the macroeconomic implications of college financing policies by explicitly taking into account of the role of college majors, an important but neglected human capital investment decision. To do so, I first seek to understand how wealth shapes college major choice. I provide new suggestive evidence on sorting patterns into majors by parental income and assess the *qualitative* relationship between various earnings characteristics of college majors and sorting by parental income. The earnings characteristics I consider move beyond average earnings, and span aspects such as earning-age profile, earnings risk, present-discounted value of lifetime earnings and inequality in average earnings across occupations for a given major. On the quantitative side, my contribution is to build a general equilibrium heterogeneous agent life-cycle model under incomplete markets, which incorporates the relevant earnings characteristics, and take the model to the U.S. data. I use the model to *quantify* the importance of earnings profile, earnings risk and non-pecuniary value of majors in driving the poorer students' major choice and study the macroeconomic implications of college subsidies.

Empirically, I document that poorer students tend to choose STEM/Health/Education majors, whereas richer students tend to choose Business/Social Science/Arts/Biology. The majors chosen by poorer students exhibit flatter earnings profile (i.e. poorer students front-load their labor earnings), lower earnings risk, and lower non-pecuniary value. Quantitatively, lower earnings risk is the driving factor for poorer students' major choice. My policy experiments have three main takeaways. First, an expansion in (unconditional) college subsidies is not sufficient to induce poorer students to switch into the majors originally taken by the rich. This is in contrast with the intuitive view that college financing policies alleviate poorer students' financial burden, thereby inducing them to choose majors currently taken by the rich. I show that for college subsidies, this is not the case. Second, keeping the total subsidies spent equalized across experiments, conditional subsidies on STEM/Health/Education generate the highest welfare gains. Third, welfare gains are not evenly distributed: individuals at the bottom quartile of the initial wealth distribution gain at the expense of the other three groups. These results highlight the importance of low earnings risk for low wealth individuals under incomplete markets and general equilibrium effect through wages and tax.

This paper opens up many fruitful avenues for future research. The framework developed in this paper is very suitable to study the impact of alternative college financing policies (e.g.: student debt forgiveness, income-based debt repayment schemes), as well as how college financing policies can respond to shifts in occupational structure resulting from technological or structural change. In particular, the idea that majors develop specific human capital and lock students into different occupations makes studying the *transitional dynamics* of college financing policies of paramount importance. The model can also be extended to incorporate richer life-cycle and intergenerational elements in order to study issues such as the complementarity between early childhood subsidies and higher education subsidies (Caucutt and Lochner (2020)), as well as occupational switching (Kambourov and Manovskii (2009)). Finally, this paper calls for more work studying the interaction between education subsidies and social insurance, as in Guvenen et al. (2021) and Krueger and Ludwig (2016).

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Online Appendix

A Data Appendix

A.1 Major classification - finer level

Table A.1 lists the 13 majors at finer level used in the empirical analysis in Section 3.2.

	Major	NLSY97	Obs.
0	no college	no college	3500
1	biology	agriculture, biology	134
2	arts	architecture, arts	223
3	business	business/management	584
4	communications	communications	152
5	computer science	computer and information science	134
6	education	education	248
7	engineering	engineering	206
8	medical science	nursing, other health, pre-dental, pre-med, pre-vet	399
9	maths/physics	maths, physical sciences	94
10	psychology	psychology	197
11	social science	criminology, economics history, political science sociology	462
12	humanities	anthropology, archaeology area studies, ethnic studies foreign languages, english philosophy, theology	304
13	home economics	home economics	36
	total		6673

Table A.1: Classification of Majors (Finer Level)

A.2 Occupation classification - finer level

Table A.2 lists the 22 occupations at finer level used in the empirical analysis in Section 3.2.

	Occupation
1	farming, forestry, fishing
2	architecture, engineering
3	life, physical, social scientist
4	management
5	artists, writers, entertainers, athletes, media
6	mathematical and computer scientist
7	education, library
8	office, administration
9	sales
10	food service
11	business/financial operations
12	personal care
13	community/social service
14	healthcare support
15	construction, extraction
16	healthcare practitioner/technician
17	protective service
18	building/grounds cleaning
19	transportation, material moving
20	production
21	installation, maintenance, repair
22	legal

Table A.2: Classification of Occupations (Finer Level)

A.3 Distribution of cognitive (maths, verbal) and non-cognitive ability by parental income group in NLSY97

Figure A.1 plots the average normalized cognitive math (AFQT maths, blue), cognitive verbal (AFQT verbal, red) and non-cognitive (Goldberg's Big Five Personality Assessment, green) by parental income quintiles. There are three main takeaways. First, cognitive skills, both maths and verbal, increase with parental income. However, Figure A.2 in Appendix A.4 shows that the distribution of cognitive skills among *college attendees* is similar across parental income groups. Second, cognitive maths and verbal skills seems highly correlated. Third, non-cognitive skills do not vary across parental income groups. These latter two observations imply that only using the AFQT (a composite score of both maths and verbal) as pre-college human capital is sufficient.

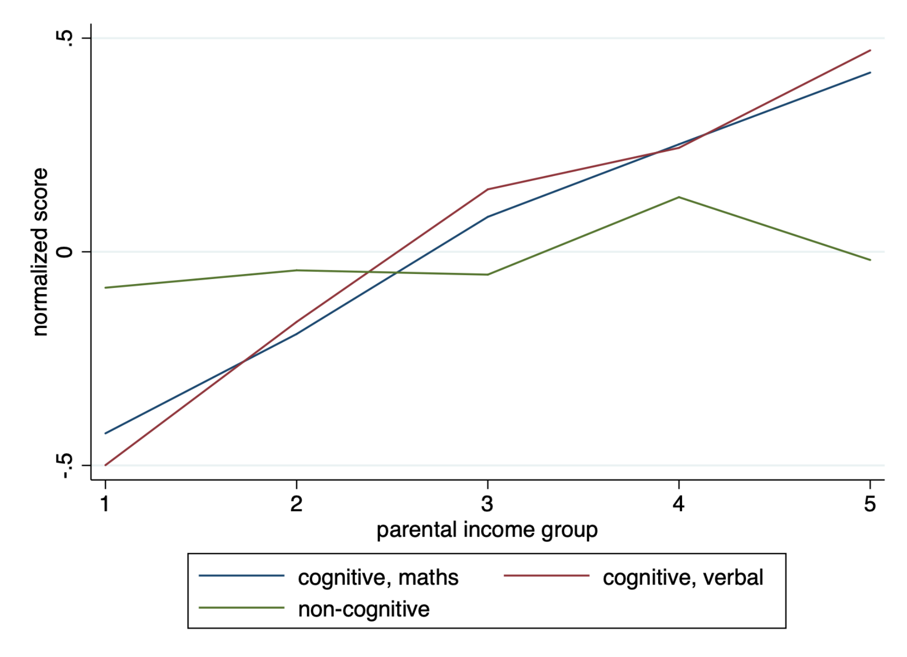
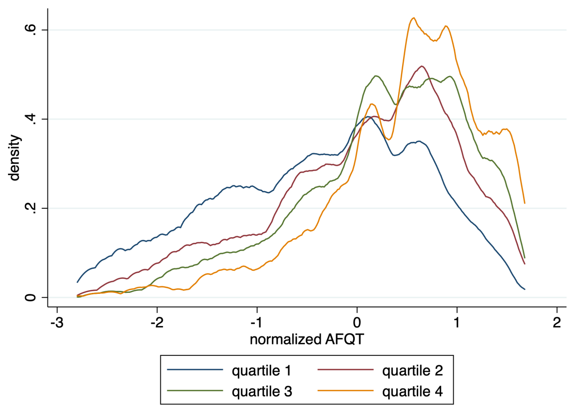


Figure A.1: Distribution of Ability Scores by Parental Income Quintiles

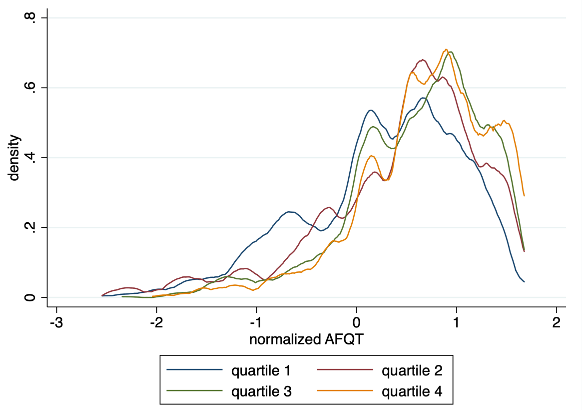
Notes: Each line plots the average normalized cognitive math (ASVAB maths, blue), cognitive verbal (ASVAB verbal, red) and non-cognitive (Goldberg's Big Five Personality Assessment, green) against parental income quintiles (x-axis) for the entire sample from the NLSY97.

A.4 Distribution of AFQT by parental income groups

Figure A.2 plots the distribution of the normalized AFQT score by parental income quartiles. The two plots indicate that although given the entire sample, the distribution of AFQT shifts more to the right the higher parental income quartile gets (Panel (a)), the distribution almost overlap across quartile groups if the sample is restricted only to college enrollees (Panel (b)). Therefore, as the focus of the paper is mainly on the intensive margin, assuming the same distribution of initial pre-college human capital across initial wealth may not be as worrisome as it seems.



(a) entire sample



(b) college only

Figure A.2: Distribution of AFQT by Parental Income Quartiles

Notes: Panel (a) is the kernel density of normalized AFQT (x-axis) and density (y-axis) by parental income quartiles for the entire sample. The blue, red, green and orange lines are for parental income quartiles 1, 2, 3 and 4 respectively. Similarly, Panel (b) is the kernel density of normalized AFQT and density by parental income quartiles, but the sample is restricted to college enrollees only.

A.5 Lifetime earnings

Figure A.3 illustrates the coefficient estimates for ϕ_{am} for two majors: computer science and social science. Computer science tends to be chosen by poorer students, whereas social science tends to be chosen by richer students. Consistent with my empirical findings on earnings profile, social science does exhibit lower initial earnings but higher earnings growth (steeper earnings profile).

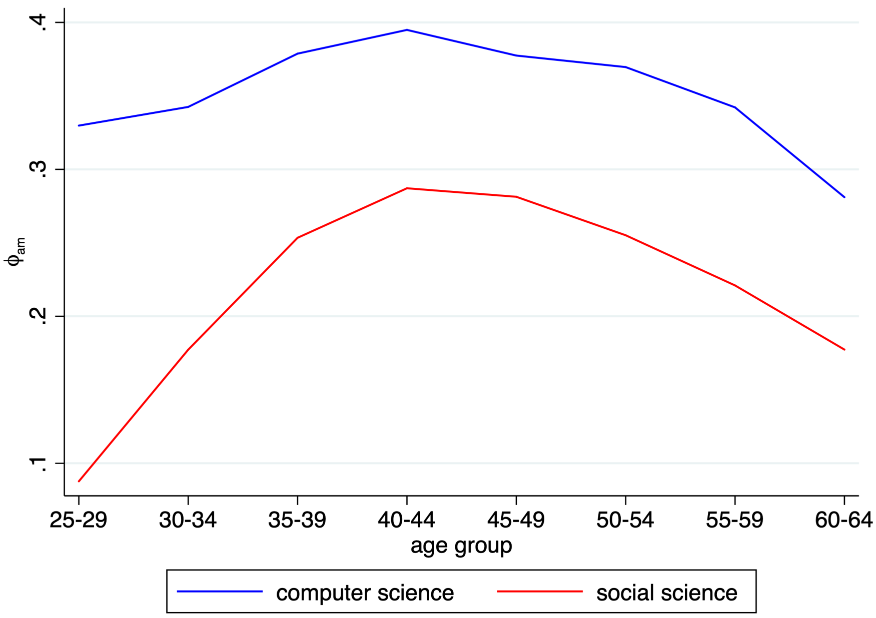


Figure A.3: Examples of ϕ_{am}

Notes: Each line plots the estimates of ϕ_{am} (y-axis) against 5-year age bins (x-axis) for computer science major (blue) and social science major (red).

A.6 Details: Occupation groups

Group 1: Architecture/Engineering, Computer/Mathematical, Healthcare Practitioner/Technician, Installation/Maintenance/Repair, Life/Physical/Social Scientist, Production.

Group 2: Business/Financial Operations, Farming/Forestry/Fishing, Management, Office/Admin, Protective, Sales, Legal.

Group 3 (relabelled as Group 0 in baseline grouping): Artists/Writers/Entertainers/Athletes/Media, Building/Grounds Cleaning, Community/Social Service, Construction/Extraction, Education/Library, Food Service, Healthcare Support, Personal Care, Transportation/Material Moving.

A.7 Major characteristics: specificity

This section discusses in more detail the idea of major specificity. A more specific (as opposed to general) major means that students in that major develop human capital (or skills) that are less widely applicable across occupations (i.e.: students develop less transferable human capital). As earnings capture the value of skills, specificity is also an earnings characteristic. Intuitively, the more unequal earnings are across occupations for a given major, the more specific this major is. I find that poorer students sort into more specific majors (i.e. majors that have a more unequal distribution of average earnings across occupations). I use two alternative ways of measuring earnings inequality across occupations for a given major, inspired by Leighton and Speer (2020).

I use the ACS data to construct measures of specificity. The large sample size of the ACS ensures sufficient number of observations at finer major $\times$ occupation level. For both approaches, I begin by estimating an otherwise standard earnings regression, occupation-by-occupation:

$$\ln w_{imt} = \alpha + X_i\Gamma + \delta_t + m_i + \epsilon_{im} \tag{26}$$

where w_{imt} is the hourly wage of individual i graduated from major m in year t, X_i is a set of demographic controls (e.g.: race, sex, martial status, years of schooling, age, age squared, US born dummy), δ_t denotes the year fixed effects, m_i is an indicator that equals to 1 if individual i graduates from major m. The key coefficients of interest are on major dummies, which I refer to as "major premium". These coefficient estimates can be interpreted as the average earnings gap between major m and non-college worker in a given occupation.

As each earnings regression is estimated occupation by occupation, the estimated major premia are not directly comparable across occupations. In order to ensure comparability, I de-mean the major premia for each occupation. As a result, the average major premium is zero for each occupation.

Finally, I compute two measures of earnings inequality of the de-meaned earnings premia, for a given major. The baseline measure is the most intuitive measure of inequality: the standard deviation of earnings premia. I compare my measure with what has been developed in the literature, Leighton and Speer (2020), who adopt a modified formula for the Gini coefficient:

$$G_m = \frac{1}{2n^2}\sum_{j=1}^{n}\Big[\sum_{k=1}^{n}|m_j - m_k|w_k\Big] \tag{27}$$

where $n = 22$ is the number of occupations, j and k both denote occupations, w_k is the share of occupation k in major m.

Figure A.4 plots the de-meaned earnings premia across occupations for two majors, computer science (red dots) and social science (blue dots). Two observations can be made. First, in line with intuition, the highest earnings occupation for computer science major is architecture/engineering, whereas computer science major has low earnings premium in sales. The reverse is true for social science major. Second, the distribution of de-meaned earnings premia is more dispersed for computer science major than for social science major. This is implies that computer science major is more specific than social science major.

Figure A.5 shows the values of major specificity using the baseline measure. Higher value means that the major develops more specific human capital. Consistent with intuition, STEM, Health and Education majors tend to be specific, whereas Business, Humanities, and Social Sciences are more general majors. Moreover, the correlation between my baseline measure if the Gini specificity is very high, equals to 0.91.

I now examine whether major specificity is related to sorting by parental income. Figure A.6 shows that poorer students sort into more specific majors.

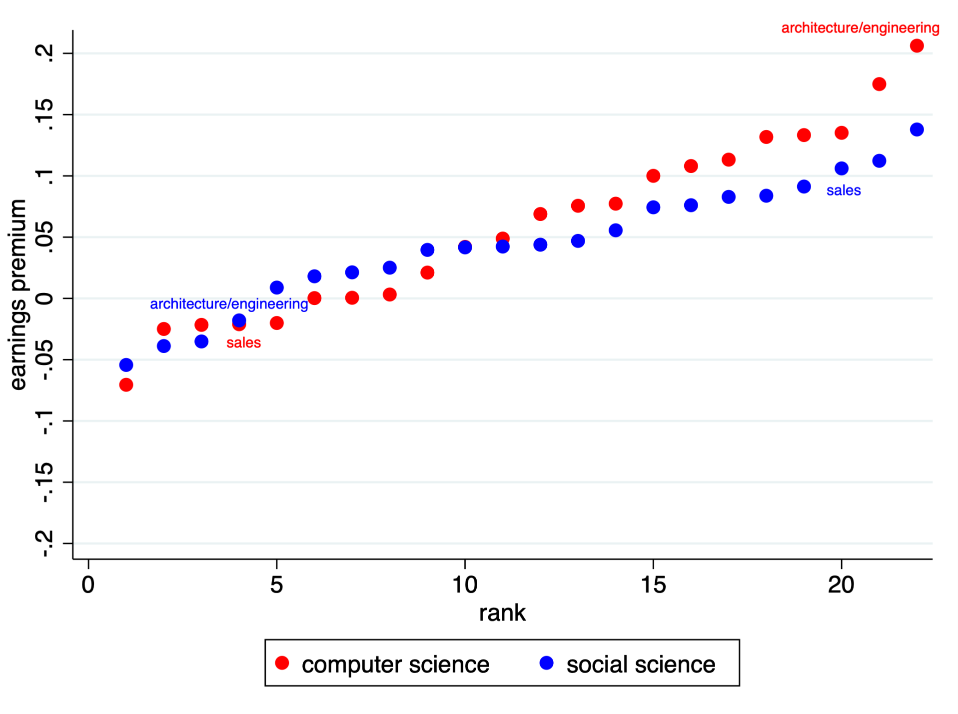


Figure A.4: Distribution of De-Meaned Occupation Premia: Examples

Notes: The figure plots the de-meaned earnings premia for two majors, computer science (red dots) and social science (blue dots). Each dot represents the de-meaned earnings premia across occupations for a given major. There are 22 occupations, hence 22 dots for a given major. For a given major, each earnings premium is sorted from the lowest to highest. x-axis denotes the rank, y-axis is the value of the de-meaned earnings premium.

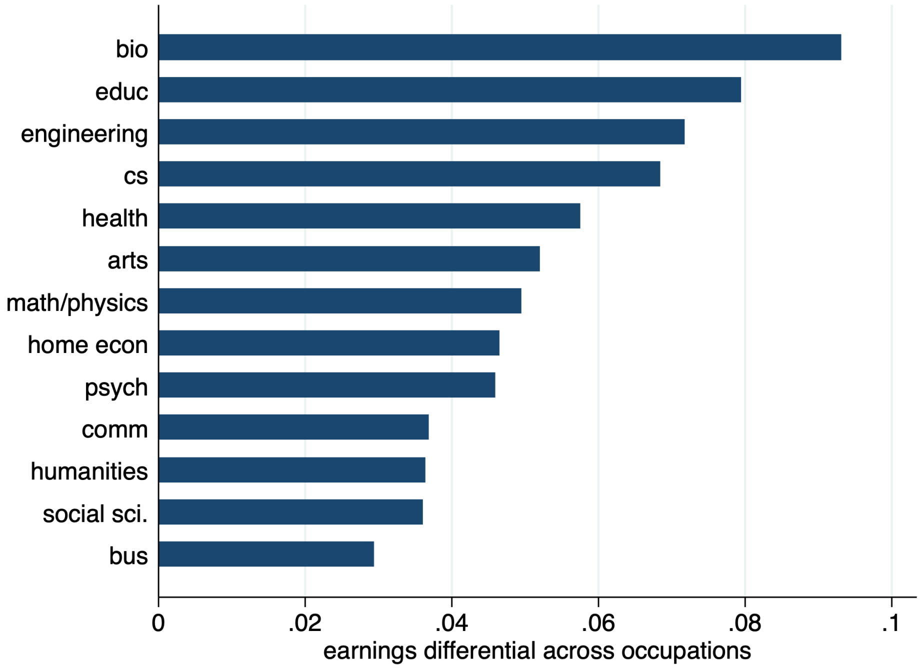
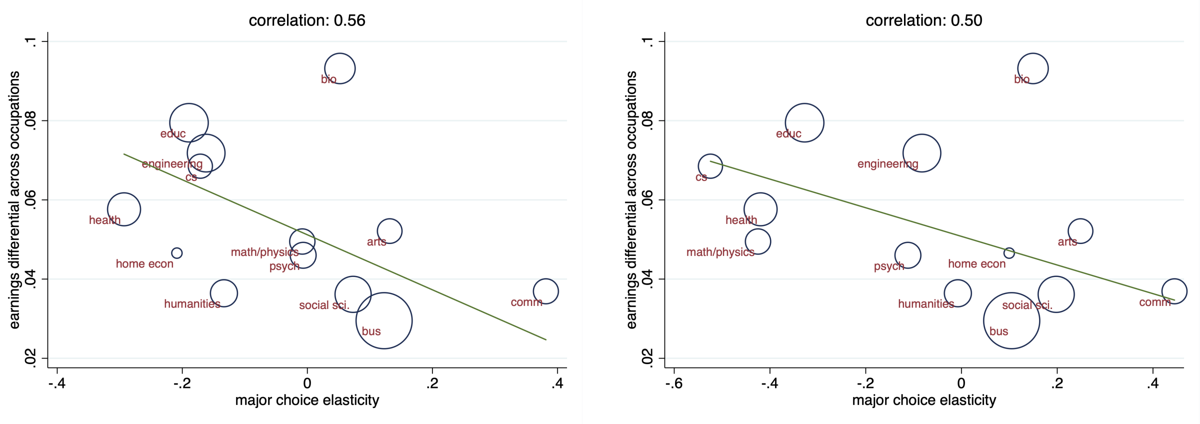


Figure A.5: Major Specificity (Baseline Measure)

Notes: Each bar represents the baseline measure of major specificity, defined as the standard deviation of demeaned earnings premia across occupations for a given major.



(a) no control

(b) + potential earnings

Figure A.6: Specificity vs. Sorting

Notes: Panel (a) shows the correlation between major specificity (y-axis) and major choice elasticity (x-axis). Negative (positive) value of major choice elasticity implies that poorer (richer) students are more likely to choose the major. Size of the circle indicates the share of students in that major.

A.8 Major cluster characteristics

I use the K-means clustering algorithm over major elasticity (derived from the NLSY97) and a wide range of major characteristics (derived from the ACS) to group 13 majors into 3 broad clusters. Figure A.7 provides an example of two major characteristics: Gini specificity (y-axis) and lifetime earnings (x-axis). Cluster 1 includes STEM (Engineering, Computer Science, Maths & Physics) and Health, which are high lifetime earnings and high specificity majors. Cluster 2 includes Business, Biology, Social Science and Communication, which are high lifetime earnings but low specificity majors. Cluster 3 includes Psychology, Arts, Humanities, Education and Home Economics, which are low lifetime earnings majors.

As the K-means clustering is over a wide range of characteristics, it is a very high-dimensional problem. I therefore report the average values of key characteristics by major clusters. Table A.3 presents the average values of major characteristics/choice elasticity within each major cluster, as well as the major cluster's share conditional on college. Cluster 1 has higher lifetime earnings, flatter earnings profile, lower earnings risk, higher specificity, and negative major choice elasticity. Cluster 2 has higher lifetime earnings, steeper earnings profile, higher earnings risk, lower specificity, and positive major choice elasticity. Cluster 3 has lower lifetime earnings, lower specificity, and close to zero major choice elasticity.

I re-run the multinomial logit regression at the 3 major cluster level, as described in Section 3.2. Table A.4 reports the major cluster choice elasticities. The results confirm that cluster 1 is mainly chosen by poorer students (negative and statistically significant), cluster 2 is mainly chosen by richer students (positive and statistically significant), and cluster 3 has no clear sorting pattern (close to zero and not statistically significant).

Given that there is no clear sorting in major cluster 3 and no clear relationship between lifetime earnings and sorting, cluster 3 (the low lifetime earnings cluster) seems redundant. Therefore, I apply K-means again to cluster 3 and divide it into two groups. I then assign each group in cluster 3 into either cluster 1 or cluster 2 based on the group average characteristics. As a result, the number of major groups in baseline is two (excluding non-college). Table A.5 reports the major characteristics. Major 1 has flatter earnings profile, lower earnings risk, higher specificity, and more likely to be chosen by poorer students. Major 2 has steeper earnings profile, higher earnings risk, lower specificity, and more likely to be chosen by richer students.

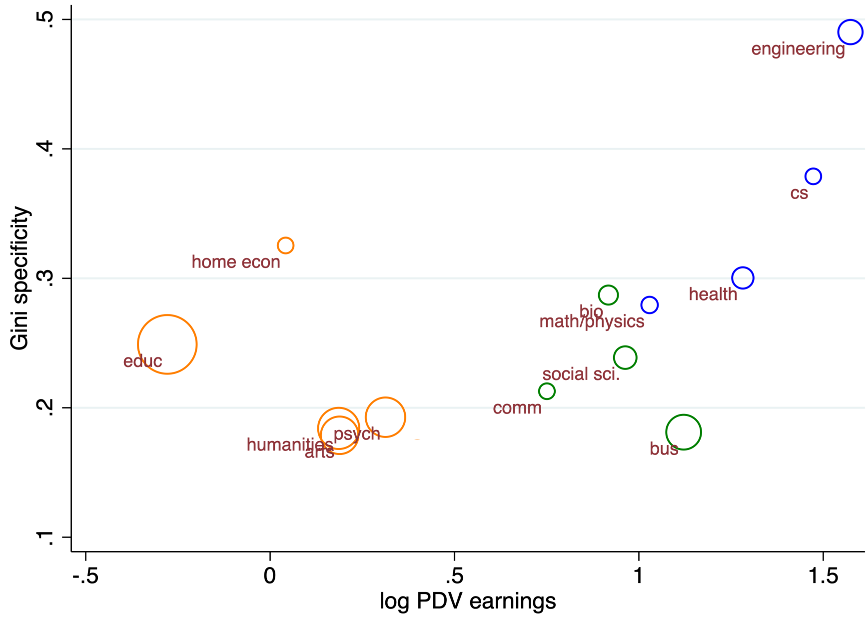


Figure A.7: K-means Clustering of Majors

Notes: This figure provides an example of two major characteristics: Gini specificity (y-axis) and lifetime earnings (x-axis). Cluster 1 majors are marked in blue (high lifetime earnings, high specificity). Cluster 2 majors are marked in green (high lifetime earnings, low specificity). Cluster 3 majors are marked in orange (low lifetime earnings).

	Cluster 1	Cluster 2	Cluster 3
log PDV of earnings	1.43	0.94	0.06
st. dev. earnings	0.57	0.63	0.56
log initial earnings	0.46	-0.12	0.19
returns to experience	0.02	0.03	0.01
Gini specificity	0.52	0.29	0.27
choice elasticity	-0.33	0.18	-0.04
major share conditional on college	0.27	0.44	0.28

Table A.3: Major Cluster Characteristics (3 Clusters)

Notes: Log PDV of earnings (relative to cluster 0, i.e. non-college), standard deviation of log residual earnings, log initial earnings, returns to experience, specificity, and choice elasticity are average value within the three major clusters. Major share conditional on college is computed for each major cluster.

	no control	control potential earnings
Cluster 1	-0.19	-0.29
	(0.051)	(0.077)
Cluster 2	0.134	0.177
	(0.025)	(0.036)
Cluster 3	-0.05	-0.04
	(0.039)	(0.055)

Table A.4: Major Cluster Choice Elasticities (3 Clusters)

Notes: Each coefficient is the major choice elasticity, defined analogously as in 1. Robust standard errors in parentheses.

	Cluster 1	Cluster 2
log PDV of earnings	0.93	0.76
st. dev. earnings	0.55	0.62
log initial earnings	0.46	-0.06
returns to experience	0.01	0.03
Gini specificity	0.47	0.27
choice elasticity	-0.32	0.13
major share conditional on college	0.39	0.61

Table A.5: Major Characteristics (Baseline Grouping)

Notes: Log PDV of earnings (relative to cluster 0, i.e. non-college), standard deviation of log residual earnings, log initial earnings, returns to experience, specificity, and choice elasticity are average value within the major group (baseline grouping). Major share conditional on college is computed for each major group.

A.9 Occupation group characteristics

Table A.6 shows the characteristics of each occupation group.

	Occ. 0	Occ. 1	Occ. 2
log PDV of earnings	-1.87	0.00	-0.28
st. dev. earnings	0.62	0.52	0.58
workers share	0.25	0.23	0.48
factor share	0.36	0.25	0.39

Table A.6: Occupation Characteristics (Baseline Grouping)

Notes: Log PDV of earnings (relative to occupation group 1) and standard deviation of log residual earnings are average value within the occupation group (baseline grouping). Workers share and factor share are computed for each occupation group.

A.10 Major-occupation shares

Table A.7 presents the raw occupational by major (not adjusted for occupational size).

	Occ. 0	Occ. 1	Occ. 2
Major 0	0.36	0.30	0.34
Major 1	0.23	0.48	0.29
Major 2	0.21	0.18	0.62

Table A.7: Raw Occupational Share by Major

Notes: Each cell in row m column j indicates the raw occupational share of j in major m from the ACS, defined as $\frac{N_{mj}}{N_m}$, where N is the number of workers.

A.11 Robustness: second measure of earnings risk

I compute a second measure of life-cycle earnings risk (a.k.a income uncertainty) following Boar (2019), defined as the standard deviation of the forecast errors of labor earnings, scaled by the expected permanent income at each age. Figure A.8 plots this measure of life-cycle earnings risk (y-axis) against age (x-axis). It is clear that compared to occupation 2 (the most likely occupation of major 2), occupation 1 (the most likely occupation major 1) has lower earnings risk (income uncertainty) at all ages.

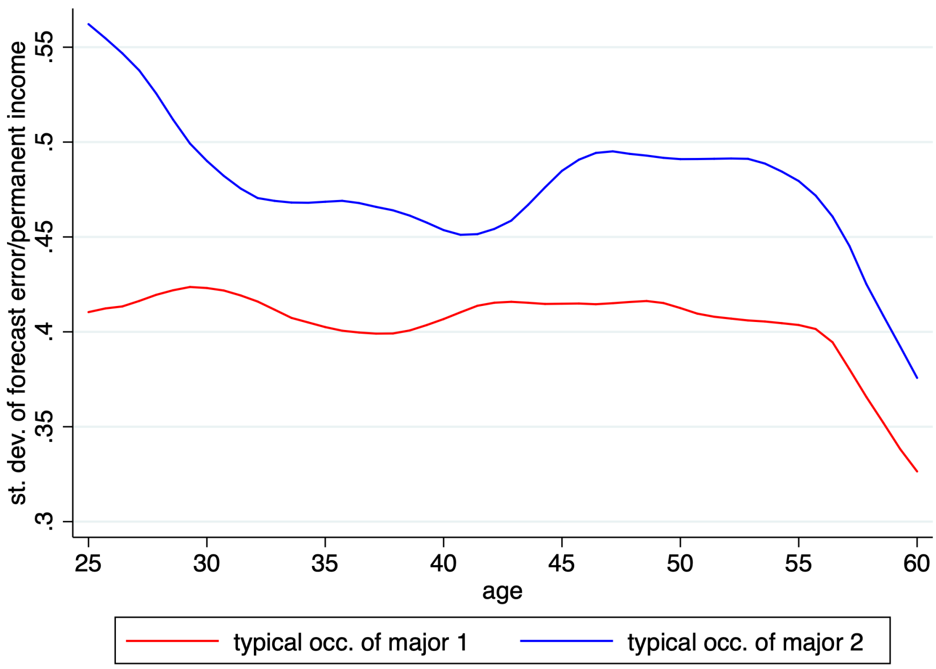


Figure A.8: Alternative Measure of Earnings Risk by Occupation Group

Notes: Each line plots income uncertainty on the y-axis (measured as the standard deviation of forecast error of labor earnings, scaled by the expected permanent income) against age on the x-axis. The red line is for occupation group 1, which is the typical occupation (most likely) of major 1. The blue line is for occupation group 2, which is the typical occupation (most likely) of major 2.

A.12 Sorting patterns by parental income groups

Table A.8 presents the raw major share (not adjusted for major size) by parental income quartile.

	Major 0 (unconditional)	Major 1 (conditional on college)	Major 2 (conditional on college)
Q1	0.73	0.39	0.61
Q2	0.58	0.36	0.64
Q3	0.46	0.34	0.66
Q4	0.28	0.31	0.69

Table A.8: Raw Major Shares by Parental Income Quartiles

Notes: Each cell represents the raw major share (not adjusted for major size, column 1: unconditional non-college share, column 2: share of major 1 conditional on college, column 3: share of major 2 conditional on college) in parental income quartile in row q.

B Model Appendix

B.1 Derivation: refinancing student debt into risk-free bonds

Let b_1 be the amount of student debt borrowed at $t = 1$. Interest rate on student debt is r_b. Student debt follows a fixed repayment scheme, where total debt plus interest must be repaid in rT periods.

Let M denote the amount of repayment. The first repayment reduces the student debt principal by $M - b_1 r_b$. Therefore, student debt principal remaining at $t = 2$ is:

$$b_2 = b_1 - (M - b_1 r_b) = (1 + r_b)b_1 - M$$

Student debt principal at $t = 3$ is:

$$b_3 = b_2 - (M - b_2 r_b) = (1 + r_b)b_2 - M = (1 + r_b)^2 b_1 - (M + M(1 + r_b))$$

Therefore, student debt principal at $t = T_r$ is:

$$\begin{aligned} b_{T_r} &= (1 + r_b)^{T_r} b_1 - (M + M(1 + r_b) + ... + M(1 + r_b)^{T_r - 1}) \\ &= (1 + r_b)^{T_r} b_1 - M \frac{1 - (1 + r_b)^{T_r}}{1 - (1 + r_b)} \\ &= (1 + r_b)^{T_r} b_1 - M \frac{(1 + r_b)^{T_r} - 1}{r_b} \end{aligned}$$

As student debt must be fully repaid in T_r periods, $b_{T_r} = 0$ implies that:

$$M = \frac{r_b (1 + r_b)^{T_r} b_1}{(1 + r_b)^{T_r} - 1}$$

Refinancing student debt a' with risk-free bonds is equivalent to having risk-free borrowing of $\tilde{a}(a')$ such that:

$$\begin{aligned} \tilde{a}(a') &= \Big(\frac{1}{1 + r} + \frac{1}{(1 + r)^2} + ... + \frac{1}{(1 + r)^{T_r}} \Big) M \\ &= \frac{1}{1 + r} \frac{1 - (1 + r)^{-T_r}}{1 - (1 + r)^{-1}} \frac{r_b (1 + r_b)^{T_r} a'}{(1 + r_b)^{T_r} - 1} \\ &= a' \frac{r_b}{1 - (1 + r_b)^{-T_r}} \frac{1 - (1 + r)^{-T_r}}{r} \end{aligned}$$

B.2 Computational algorithm

1. Discretize the state space: 150 grids on the asset space with more points closer to the borrowing constraint, and discretize the AR(1) process on human capital following Fella, Gallipoli and Pan (2019)[27].

2. *Outer loop:* Start with some initial guesses for the parameters to be calibrated using the SMM, as well as an initial guess for a_{p25}.

3. *Inner loop - step 1:* Guess a set of prices $\{w_0, w_1, w_2, r\}$. Solve the optimal individual policy functions and value functions under these prices. From $T = 12$, solve the value function from backwards by finding the optimal policies at each age t using golden section search.

4. *Inner loop - step 2:* Compute the ergodic distribution, starting from zero initial assets and iterate until convergence.

5. *Inner loop - step 3:* Update the set of prices $\{w_0, w_1, w_2\}$ using occupational labor market clearing, update r using asset market clearing.
   Baseline equilibrium: Find exogenous government spending G that ensures government budget balance. Find productivity $\bar{A}$ that ensures w_3 to be normalized to 1.
   Counterfactual equilibrium: Take G and $\bar{A}$ in the baseline equilibrium as given, find τ_0 that satisfies government budget balance.

6. *Outer loop:* Compute the model counterparts of the moments to be matched in the calibration. Update the guesses from Step 1.

[27] As the volatility of the initial human capital draw $\sigma_{\eta,j}$ is different from the volatility of human capital draw aftewards σ_j, the AR(1) is non-stationary.

B.3 Parameterization: income process

These parameters of the income process are estimated in two steps:

1. directly estimated from data: $\Gamma_j, \lambda_j, \log \bar{h}_{mj}$

2. mininum distance estimator to match moments: $\sigma_{\eta,j}, \rho_j, \sigma_j$

As each period is 5 years, I group observations over 5 years. To obtain the occupation-specific life-cycle component of earnings Γ_j, I estimate the earnings profile of each occupation by regressing log annual labor earnings on age, age squared, sex, and race from the PSID. In order to correct for selection into work, I use a Heckman-selection estimator. More specifically, I construct Inverse Mills ratios by estimating the participating equation taking into account of sex, marital status, number of children, and year-region fixed effects. Table B.1 reports the estimates.

I then use the NLSY79/97 to estimate the return to AFQT λ_j and the increase in occupational human capital by major $\log \bar{h}_{mj}$, occupation by occupation. I combine the NLSY79 and NLSY97 to increase the sample size. I apply the methodology of Altonji, Bharadwaj and Lange (2019) in order to ensure comparability across AFQT scores. More specifically, I first remove the life-cycle component of earnings using estimates of Γ_j. I then regress the log of residual earnings on sex, marital status, race, number of household members, year fixed effects, and most importantly, normalized AFQT and major dummies. The coefficients for the normalized AFQT and major dummies are therefore λ_j (Table B.2) and $\log \bar{h}_{mj}$ (Table 5), respectively.

For each occupation, I remove the Γ_j, λ_j, and $\log \bar{h}_{mj}$ components of earnings. I then calculate moments on the variances and autocovariances (one lag) of log residual earnings, as well as the standard deviation of log (residual) earnings growth. These moments are used as calibration targets to pin down $\sigma_{\eta,j}, \rho_j$, and σ_j using the minimum distance estimator. The estimates and their corresponding moments are reported in Tables 6 and 7.

	Occ. 0	Occ. 1	Occ. 2
Age	0.212	0.181	0.263
	(0.015)	(0.030)	(0.015)
Age^2	-0.02	-0.01	-0.02
	(0.001)	(0.003)	(0.001)

Table B.1: Age Profile by Occupation

Notes: Robust standard errors in parentheses.

	Occ. 0	Occ. 1	Occ. 2
AFQT	0.120	0.153	0.172
	(0.006)	(0.008)	(0.007)

Table B.2: Return to AFQT by Occupation

Notes: Robust standard errors in parentheses. The regressions include year fixed effects.

B.4 Additional results: major choice by initial wealth quartiles

Figure B.1 and B.2 plot the major choice probabilities of students from the second lowest quartile (p25-p50) and third quartile (p50-p75) in the steady-state initial wealth distribution, respectively. As the major choice probabilities of students from the third quartile is the same as those from the fourth quartile (p75-p100), Figure B.2 also depicts the major choice of the fourth quartile.

The second lowest quartile students respond slightly to college subsidies. This is because subsidies are distributed to the bottom quartile students in the steady state initial wealth distribution, and the 25 percentile cut-off is higher as college subsidies increase. The top two quartiles do not respond. This is because (i) these students are not eligible for college subsidies as they are only given to the bottom quartile, and (ii) increase in total subsidies spent is very small, so general equilibrium changes in prices are not enough to induce a different choices of major. As a result, colleges subsidies have limited impact on the choices of richer individuals.

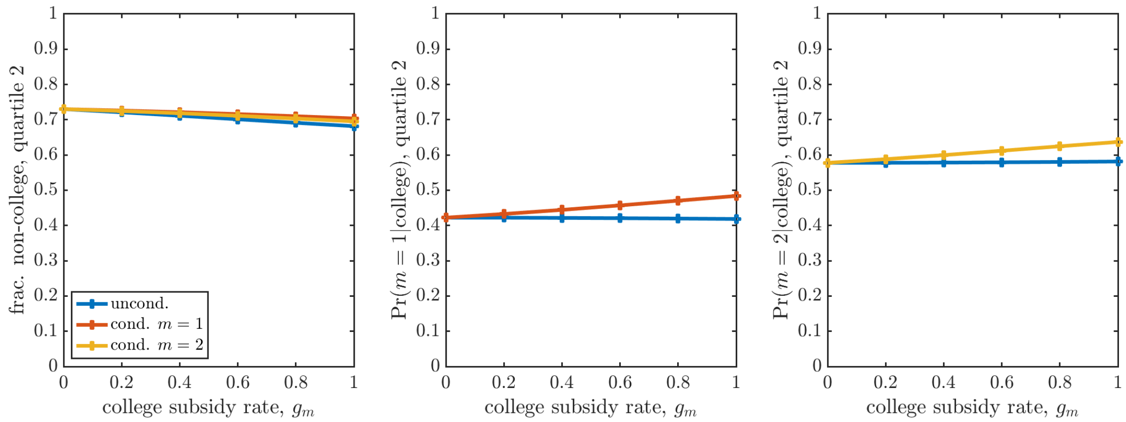


Figure B.1: Major Choice of the Second Quartile (p25-p50), Initial Wealth

Notes: Each line plots the major choice probabilities for the second quartile (p25-p50) of the initial wealth steady state distribution. The blue line is under unconditional college subsidies, $g_1 = g_2$. The red line is under college subsidies conditional on major 1, $g_2 = 0$. The yellow line is under college subsidies conditional on major 2, $g_1 = 0$. x-axis is the level of college subsidy rate g_m. All are steady-state comparisons. The left panel is the non-college share. The middle panel is the share of major 1 conditional on college. The right panel is the share of major 2 conditional on college.

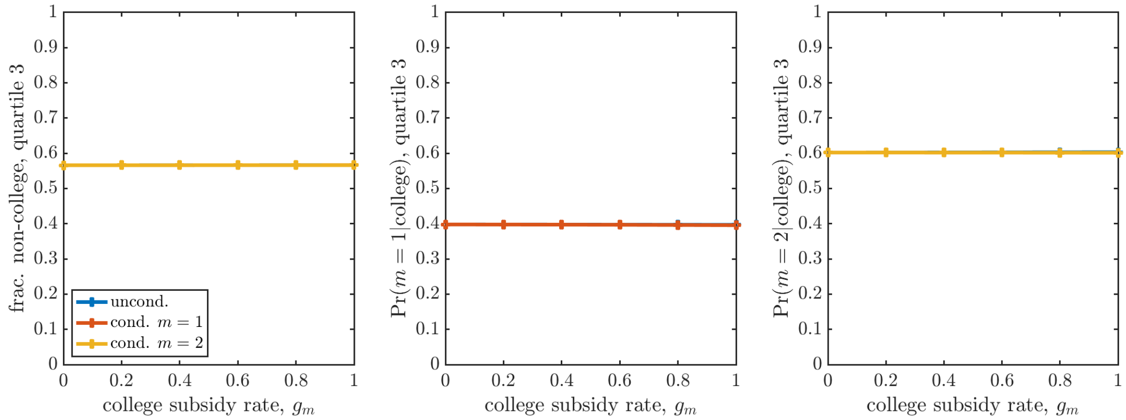


Figure B.2: Major Choice of the Third/Fourth Quartile, Initial Wealth

Notes: Each line plots the major choice probabilities for the third/fourth quartile of the initial wealth steady state distribution. The blue line is under unconditional college subsidies, $g_1 = g_2$. The red line is under college subsidies conditional on major 1, $g_2 = 0$. The yellow line is under college subsidies conditional on major 2, $g_1 = 0$. x-axis is the level of college subsidy rate g_m. All are steady-state comparisons. The left panel is the non-college share. The middle panel is the share of major 1 conditional on college. The right panel is the share of major 2 conditional on college.

B.5 Additional results: college subsidies

Table B.5 summarizes the macroeconomic effects of the three budget-equivalent college subsidies schemes: unconditional, conditional on major 1, and conditional on major 2.

	$g_1 = g_2 = 0.70$	$g_1 = 0.92, g_2 = 0$	$g_1 = 0, g_2 = 0.84$
non-college share	0.60	0.61	0.60
major 1 share in college	0.40	0.47	0.35
major 2 share in college	0.60	0.53	0.65
efficiency wage of occupation 0 (w_0)	0.36	0.38	0.28
efficiency wage of occupation 1 (w_1)	-0.26	-0.69	0.18
efficiency wage of occupation 2 (w_2)	-0.13	0.21	-0.33
risk-free interest rate (r)	-0.009	-0.027	-0.012
average tax rate (τ_0)	-0.021	-0.028	-0.013
output	0.72	0.78	0.51
income inequality	0.35	0.35	0.17
initial wealth inequality	1.61	1.44	1.00

Table B.3: Quantitative Results for College Subsidies

Notes: Non-college share and conditional major shares are expressed in levels. r and τ_0 are expressed as level changes relative to the baseline. Other variables are expressed as percentage changes relative to the baseline.

B.6 Additional results: tuition pricing

This section examines steady state outcomes under the assumption that college subsidies are given to all students, regardless of initial wealth. This case is conceptually the same as a tuition pricing policy. I first fix the college subsidies to be conditional on major 1 and equals to 1 (i.e.: free tuition in major 1). I then search for the g_m that equalizes the total subsidies spent across experiments. If college subsidies are given to all students, the following g_m values yield the same total subsidies spent in equilibrium: unconditional subsidies at $g_1 = g_2 = 0.6$, conditional subsidies on major 1 at $g_1 = 1, g_2 = 0$, and conditional subsidies on major 2 at $g_1 = 0, g_2 = 0.8$.

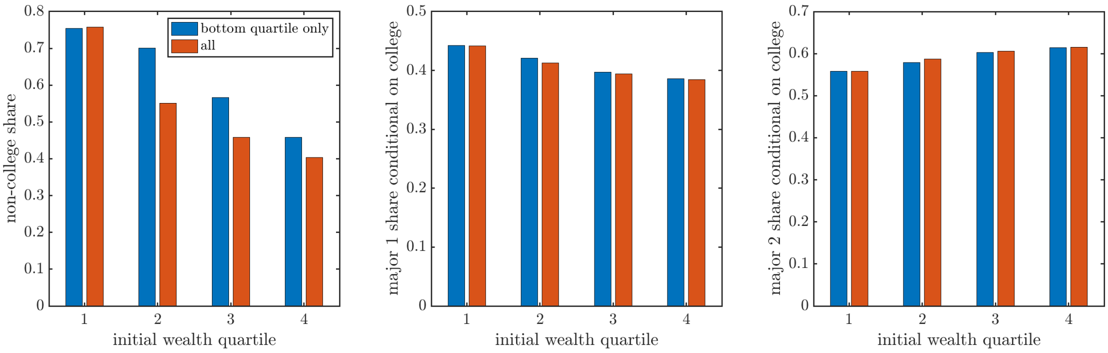
Table B.4 summarizes the quantitative results of key aggregate variables across experiments. I compare college subsidies distributed to all students (Panel (b)) vs. subsidies at the same rates but only distributed to the bottom quartile (Panel (a)). Note that if subsidies are distributed to the bottom quartile only, the underlying total subsidies spent are not necessarily equalized across these three experiments. The effects are stronger if the subsidies are distributed to all students.

Figure B.3 depicts major shares (from left to right in each panel: non-college share, major 1 share conditional on college, major 2 share conditional on college) by steady-state initial wealth quartile. The blue bar is under the assumption that college subsidies are given to students from the bottom quartile of the initial wealth distribution. The red bar is under the assumption that college subsidies are given to all students, regardless of wealth, similar to tuition pricing policies. As college subsidies are expanded to all students, unconditional subsidies do not change major choices at the intensive margin by much. However, students from the three upper quartiles do respond strongly to conditional subsidies on majors once they become eligible.

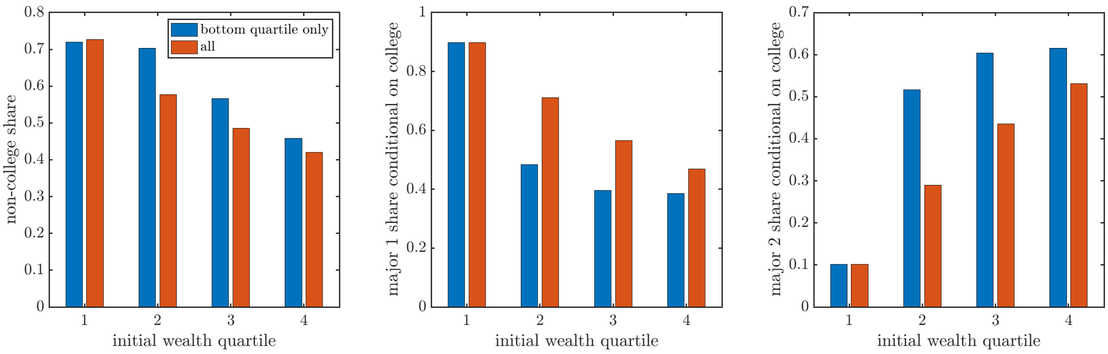
	$g_1 = g_2 = 0.6$	$g_1 = 1, g_2 = 0$	$g_1 = 0, g_2 = 0.8$
Panel (a): bottom quartile only			
non-college share	0.61	0.59	0.61
major 1 share in college	0.40	0.48	0.35
major 2 share in college	0.60	0.52	0.65
efficiency wage of occupation 0 (w_0)	0.26	0.47	0.25
efficiency wage of occupation 1 (w_1)	-0.20	-0.81	0.18
efficiency wage of occupation 2 (w_2)	-0.10	0.23	-0.31
risk-free interest rate (r)	-0.004	-0.036	-0.009
average tax rate (τ_0)	-0.016	-0.030	-0.012
output	0.58	0.91	0.46
income inequality	0.25	0.41	0.15
initial wealth inequality	1.23	1.71	0.89
Panel (b): all			
non-college share	0.60	0.40	0.74
major 1 share in college	0.40	0.60	0.26
major 2 share in college	0.60	0.40	0.74
efficiency wage of occupation 0 (w_0)	0.98	1.36	0.85
efficiency wage of occupation 1 (w_1)	-0.47	-2.31	0.78
efficiency wage of occupation 2 (w_2)	-0.36	0.57	-1.02
risk-free interest rate (r)	-0.06	-0.08	-0.07
average tax rate (τ_0)	0.08	0.07	0.09
output	2.14	2.23	1.68
income inequality	0.60	0.97	0.27
initial wealth inequality	3.73	3.66	2.48

Table B.4: Quantitative Results for Tuition Pricing

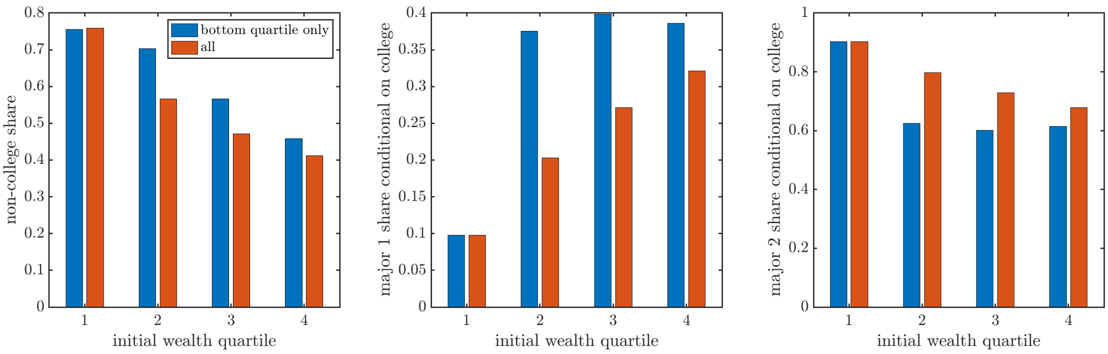
Notes: Non-college share and conditional major shares are expressed in levels. r and τ_0 are expressed as level changes relative to the baseline. Other variables are expressed as percentage changes relative to the baseline. Panel (a) is under the assumption that college subsidies are given to students from the bottom quartile of the steady-state initial wealth distribution. Panel (b) is under the assumption that college subsidies are given to all students, regardless of initial wealth. This case is conceptually the same as a tuition pricing policy.



(a) unconditional subsidies: $g_1 = g_2 = 0.6$



(b) conditional subsidies on major 1: $g_1 = 1, g_2 = 0$



(c) conditional subsidies on major 2: $g_1 = 0, g_2 = 0.8$

Figure B.3: Major Choice by Initial Wealth Quartile: Bottom Quartile Only vs. All

Notes: The figure depicts major shares (from left to right in each panel: non-college share, major 1 share conditional on college, major 2 share conditional on college) by steady-state initial wealth quartile (x-axis). Each panel represents unconditional subsidies (Panel (a)), conditional subsidies on major 1 (Panel (b)), and conditional subsidies on major 2 (Panel (c)), respectively. The blue bar is under the assumption that college subsidies are only given to students from the bottom quartile of the initial wealth distribution. The red bar is under the assumption that college subsidies are given to all students, regardless of wealth, similar as tuition pricing policies.