The Returns to College Major Choice: Average and Distributional Effects, Career Trajectories, and Earnings Variability*

Rodney J. Andrews
The University of Texas at Dallas and NBER

Scott A. Imberman
Michigan State University and NBER

Michael F. Lovenheim
Cornell University and NBER

Kevin Stange
The University of Michigan and NBER

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ABSTRACT

Motivated by the large returns to skill in the labor market, there is a growing body of research examining labor market returns to college major. Prior research focuses almost exclusively on mean effects and pays little attention to earnings growth and variability. Using data from Texas on public K-12 students followed through college and into the labor market, we find that the focus on mean differences mask important features of the returns to college majors. First, earnings growth varies with major choice, making returns sensitive to the experience distribution of the sample. Second, quantile treatment effect estimates show considerable cross sectional differences in earnings returns. Third, major choice affects earnings variability within workers over time. We use our results to simulate a lifecycle utility model and compare mid-career utility and mean earnings returns across fields while highlighting the important role of risk preferences. For four-year students, utility returns align with earnings returns, and utility returns increase as students become more risk averse. Results for two-year students are broadly similar, though risk preferences interact with cross-sectional earnings returns variation in complex ways that highlight the importance of different dimensions of risk in driving the returns to major choice.

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Introduction

The return to skill in the labor market is at historically high levels as the US industrial base continues to shift away from manufacturing and towards services, which requires different skills (Autor 2014; Deming 2017); increasingly, even middle-class jobs require some postsecondary education. Consequently, postsecondary investment has grown considerably, with the college enrollment rate of recent high school graduates increasing by 15 percentage points, fall enrollment more than doubling, and the number of undergraduate degrees tripling since 1970.[1] The average returns to college have grown as well, reflecting the demand for high-skilled labor. However, these high average returns mask important heterogeneity across a number of dimensions (Lovenheim and Smith, 2023), including major or course of study.

Understanding the returns to college major is critical, as major choice is the primary process through which individuals invest in specific forms of human capital (Hemelt et al. 2021). Even among similar students, there is large variation in earnings across students with different majors (Arcidiacono, 2004; Hamermesh and Donald, 2008; Altonji, Blom and Meghir 2012; Andrews, Imberman and Lovenheim 2017; Andrews and Stange, 2019). In fact, the mean earnings differences across majors are at least as large as the earnings gap between high school and college graduates (Altonji, Blom and Meghir 2012). Information on the consequence of college majors is useful to students and policy-makers, who can use it to improve postsecondary choices (Wiswall and Zafar, 2015, 2021) or direct resources to higher-return fields, respectively. Indeed, recently several states such as Mississippi and West Virginia have moved to scale back certain postsecondary programs based on concerns over low returns.

Prior research focuses almost exclusively on mean effects of major at specific ages.[2] In this paper, we provide new evidence on three additional dimensions of the returns to major: (1) earnings growth with experience, (2) cross-sectional variation across workers; and (3) short-term within-worker variance. The first type of variation is important because majors can affect the trajectory of earnings, which makes mean estimates sensitive to the age at which individuals are observed. The second type of variation could be considered ex-ante risk of choosing a major:

[1] These tabulations come from the Digest of Education Statistics, Tables 302.10, 303.10, and 318.10.

[2] Notable exceptions are Webber (2014, 2016), who estimate returns at multiple ages from a cohort that finished college forty years ago, and Hershbein and Kearney (2014), Hershbein, Harris and Kearney (2014), and Choi et al. (2023), who examine differences in earnings growth across majors but without controls for selection.

mean returns may shift the entire earnings distribution similarly or shift specific parts of the distribution that only are relevant for a small number of workers. The third source of variation reflects within-worker variability of earnings, which may differ across majors. Fluctuations in earnings can be harmful to families if they lack full access to credit and are risk-averse (Zeldes 1989; Stephens 2003; Chetty 2008). We combine these three sources of variability using a life-cycle utility model to determine how these sources of variability impact the welfare consequences of major choice.

We analyze administrative data linking seven cohorts of Texas public high school graduates to their postsecondary records and up to 20 years of quarterly earnings records in the state. These data provide a sample size, wealth of pre-collegiate information, within-year earnings variation, and long-term follow-up that are not available in any other US-based dataset. We estimate returns separately for those attending a four-year and a two-year college, aggregating majors into up to eleven groups plus undeclared. Our selection-on-observables method compares students with similar pre-collegiate test scores and student demographics who graduated from the same high school in the same year and who attended the same college (from the same high school cohort) but who differed in major choice. While this approach makes the strong assumption that these observables are sufficient to account for all differences across students in potential labor market outcomes, our estimates are identified off weaker assumptions than prior selection-on-observables analyses of the returns to college majors. Despite its growing use in other settings, there are few opportunities to use a regression discontinuity (RD) approach in the US across multiple fields and institutions.

We present several findings that advance our understanding of how major choice affects earnings and well-being as well as the role of risk in driving the returns to college major. First, we find that the returns to college major choice vary substantially across majors and with experience in heterogeneous ways. Quarterly returns (relative to liberal arts) range from $983 in communications to $7,901 in engineering and architecture 16-20 years after high school (inflation adjusted to 2016 dollars). The returns to biology and health grow the most over time, increasing by a factor of 12.7 (from $413 to $5,655) over a 10 to 15-year period. The returns to physical science and math and communications increase by over 400%, while relative returns to business and economics, vocational, and engineering and architecture increase by 100-200%.

Among two-year students, relative returns vary from -\$1,247 (communications) to \$1,065 (vocational) 16 to 20 years post-high school. Growth rates are smaller than in the 4-year sector, with some increasing and some decreasing relative to liberal arts over time: communications returns decrease by almost 300% and IT returns decline by a factor of 15.5, while engineering and architecture, business and economics, and social science returns increase by 33-100%.

Second, quantile treatment effect estimates (DiNardo, Fortin, and Lemieux 1996; Firpo 2007) indicate there is substantial variation in how major choice influences the distribution of earnings, with some majors shifting the earnings distribution relatively uniformly and others – notably fields that tend to have higher mean earnings - generating much larger effects at the top of the distribution. This suggests the mean effects embed substantial (and differential) ex-ante risk for students. Third, college majors have a modest effect on the within-worker variation in earnings, measured by the coefficient of variation of earnings relative to predicted earnings for each worker. Most majors lead to lower earnings variability than liberal arts; however, the magnitude of the effect varies across majors. Earnings variability effects tend to be larger in the four-year than in the two-year sector.

Finally, to bring together our various findings, we embed our estimates in a constant relative risk aversion (CRRA) lifecycle utility model. The results from these simulations show effects of major choice on cumulative utility through the late 30s and allow us to compare utility effects with longer-run mean earnings effects. Our estimates show that mean earnings 16 to 20 years after high school track utility closely, with some notable differences driven by the time path of earnings returns. Earnings returns align with utility returns more in the four-year than in the two-year sector, especially when risk aversion is low. In both sectors, our results highlight the importance of risk in determining the returns to major choice. Risk preferences, as measured by the coefficient of relative risk aversion, ex-ante risk, as measured by the shape of the quantile treatment effect estimates, and within-worker earnings variance, interact to have large effects on measured utility returns. In the four-year sector, higher risk aversion tends to increase the gap between high and low mean return fields because of higher earnings levels that protect against earnings variance. In the two-year sector, the effect of increasing risk aversion is more mixed and depends on the shape of the QTE curves and the sign of the earnings variance effect. We are the first in the literature to show the importance of risk preferences and cross-sectional earnings risk in the returns to major choice, which provides a framework for future researchers to examine these returns more comprehensively.

This paper builds on a growing body of work on the returns to college major, which is reviewed by Altonji, Blom, and Meghir (2012), Altonji, Arcidiacono, and Maurel (2016), and Lovenheim and Smith (2023). In the four-year sector, recent work exploits major admission cutoffs using an RD, finding a consistent story of large causal effects of major choices on mean earnings. This work focuses on centralized admission cutoffs in international contexts (Hastings, Nielson and Zimmerman 2013; Kirkebøen, Leuven and Mogstad 2016) or a single major in US institutions (Andrews, Imberman and Lovenheim 2017; Bleemer and Mehta 2022). Estimating RD models for a wide set of majors in the US is not possible given decentralized admissions and the fact that binding cutoffs are confined to a small number of fields and institutions. Work in the two-year sector primarily compares earnings before and after enrollment using individual fixed effects (Jepsen, Troske and Coomes, 2014; Stevens, Kurlaender and Grosz 2019). These papers show wide variation in the returns to AA degrees, with particularly large returns to health degrees. This literature necessarily focuses on older students who have earnings prior to school, making comparisons difficult with the studies focused on the four-year sector.

Our paper contributes to this growing literature on the returns to college major by moving beyond an analysis of mean effects at specific ages and by examining four- and two-year institutions within the same context and using the same approach to facilitate comparisons. We provide new evidence on how majors contribute to post-collegiate earnings growth, how majors shift the cross-sectional distribution of earnings, how majors influence the within-worker variance in earnings, and how these factors combine to influence the utility consequences of major choice. Prior analysis uses workers with different levels of experience, ranging from 8 or 10 years after enrollment (Kirkebøen, Leuven and Mogstad, 2016; Bleemer and Mehta, 2022) to the early- and mid-thirties (Arcidiacono, 2004; Andrews, Imberman, and Lovenheim, 2017). Heterogeneity in the earnings paths associated with different college majors, such as documented by Martin (2021) and Choi et. al. (2023), makes it challenging to compare results across studies.

Prior work also does not examine distributional effects, and mean effects may be a poor reflection of earnings returns for the typical student. Previous research has shown heterogenous returns to institutional quality (Andrews, Li and Lovenheim, 2016) and of majors by occupation

(Leighton and Speer, 2020; Schanzenbach, Nunn, and Nantz, 2017). These analyses do not identify how college majors shift the entire distribution of earnings, however. No prior study has addressed the potential for major choice to alter within-year earnings variability for individuals.[3] Such fluctuations in earnings can be harmful to families if they lack full access to credit and "buffer stock" savings and are risk-averse or credit constrained. For example, Dillon (2018) finds that people are willing to enter occupations with significantly lower salaries to avoid earnings variability due to risk aversion. Finally, we add to the literature by using our estimates to simulate a lifecycle utility model that allows us to compare utility and earnings returns as well as highlights the role of risk in driving the returns to college major choice.

Taken together, our results highlight the importance of understanding these various dimensions of the returns to college major both to help students make more informed major choice decisions and enable policymakers and higher education administrators to make better resource allocation decisions.

I. Data, Sample, and Measures

a. Data and Analysis Variables

We estimate the labor market returns to college majors using administrative data from three sources: the Texas Education Agency (TEA), the Texas Higher Education Coordinating Board (THECB), and quarterly earnings from the Texas Workforce Commission (TWC). These data follow all Texas students from public secondary school through college and into the workforce, provided individuals remain in Texas and attend public colleges and universities.

From the TEA data, we construct a sample of all graduates from public high schools in the state from 1996 to 2002, including the school location, state standardized test scores in math and English, and a host of demographic and educational characteristics. This sample of high school graduates is merged with data from the THECB, which contain detailed information about college enrollment and major in each semester and whether and when a degree was earned from

[3] Delaney and Deveraux (2019) exploit education expansions and find that more education lowers earnings volatility. They do not examine college major effects, however. Using a measure of annual volatility, Christiansen, Joensen, and Nielsen (2007) find inconsistent patterns of risk-return tradeoffs across field-level combinations, although the results are difficult to interpret without controls for academic preparation that influences students' investment opportunities.

each institution. These data are comprised of all students who enroll (completers and non-completers) in a public two-year or four-year postsecondary institution in Texas. Due to the dominance of public postsecondary schools in the state, this encompasses most college students.

We partition students into two mutually exclusive samples, one for two-year students and one for four-year students. Classifying students by sector and major is not straightforward, given the diversity of pathways students take through college (Andrews, Li, Lovenheim, 2014). We aim to capture the most salient postsecondary experience to employers when students end their education. The labor market value of the most salient degree earned (or attempted) is of high importance for students when making decisions about the field of study. Information on program earnings provided by the College Scorecard (nationally) and many state websites reflect this view, by focusing on degree at the time of completion rather than entry. With that in mind, we assign students to sector and major based first on their highest degree earned and then based on their most recent sector of enrollment. Any students who earn a bachelor's degree (BA or BS) at a Texas public institution are included in the 4-year sample, regardless of where they began college or if they subsequently enrolled in other sectors after earning a degree. Students who earned an Associate degree (AA) but no bachelor's are included in the 2-year sample, even if they enrolled in a four-year institution before or after earning an AA. Our assumption is that students' AA degree will be more salient to employers than their four-year enrollment that did not lead to a credential. Students who do not earn a bachelor's or associate's degree are assigned to the sector of their last enrollment, regardless of where they started. This ensures that we are focusing on the most observable and recent degree or enrollment information that employers may see and that likely determines the skills workers bring to the labor market.

The drawback of classifying students in this way is that we do not capture the potential option value of enrolling in different two-year programs (Stange 2012). If some community college majors are better at facilitating transferring to and graduating from four-year colleges, these returns will not be reflected in our estimates. Though 30% of students who begin their career at a community college transfer to a four-year school in Texas (Andrews, Li, and Lovenheim 2014), there is no relationship between major choice and transferring behavior (Andrews, Imberman, and Lovenheim, 2017). We focus on the return to the highest degree received (or highest level of enrollment) to examine how specific degrees are valued in the labor market. This information is valuable to students making enrollment decisions and to higher education administrators. There are other dimensions of returns that this approach will not capture, such as the option value of major choice and effects on non-earnings outcomes. While important, they are beyond the scope of our analysis.

Students' majors are assigned in a similar way as sector, first based on major of their highest degree and then, for non-completers, based on last observed major. We aggregate four-year students into one of 11 major groups based on a combination of their specific 2- and 4-digit CIP codes: agriculture, communications, IT, vocational, engineering and architecture, biology and health, physical sciences and math, social sciences (excluding economics), business and economics, and undeclared. Two-year majors are similarly grouped, however there also is a 2-year education major; no such major is offered by Texas public four-year colleges. Appendix Table A-1 lists the detailed majors included in each broad major category.

Labor market outcomes are constructed from quarterly earnings records through second quarter of 2018 for each student who works in Texas, except for those who work for the Federal Government, postal service, or are self-employed. These workers are excluded from the earnings data because they are not covered by the state UI system. Thus, we cannot distinguish between those who are unemployed, self-employed, not in the labor force, or working outside of Texas. In general, out-of-state attrition can bias estimates of earnings differences across institutions and fields since migration tends to be correlated with earnings and is differential across programs (Foote and Stange, 2022). In prior work, we do not find such selection to be problematic (Andrews, Li and Lovenheim 2016; Andrews, Imberman and Lovenheim 2017, 2020), and the extent of this bias appears low in Texas specifically due to relatively low out-migration (Foote and Stange, 2022).

To reduce bias associated with out-of-state migration, we only include quarterly earnings records that occur during students' in-state employment window, which we define as the time spanning the first non-zero earnings record after leaving college and the last non-zero earnings record. This excludes any periods of non-employment immediately after school and at the end of our sample, which would include records from those who have permanently left the state. We also exclude quarters in which students are enrolled in a public postsecondary institution in Texas, which ensures we are not attributing low earnings during graduate school to a specific major. While we are unable to observe enrollment in graduate schools outside of Texas, this would bias our estimates only to the extent that majors differentially sort to such institutions relative to in-state publics for graduate school. Finally, we only include earnings observations at least 6 years after high school graduation. Quarters with no earnings records that are within the in-state earnings window and meet our inclusion criteria are imputed to be zero and included in our earnings estimates. Earnings are converted to real 2016 dollars throughout the analysis.

Bias from exiting the earnings sample only is problematic if it is differential by major. Online Appendix Table A-2 directly examines such differences in attrition by estimating equation (2) below for different measures of inclusion in the sample. Specifically, we estimate the effect of major choice on the number of non-zero earnings quarters, the number of quarters with imputed zero earnings, and the likelihood an individual leaves the sample (according to our definition above). In both the two-year and four-year sectors, there are at most minor differences in the number of quarters with non-zero earnings by major, with estimates ranging from 1-3 quarters in the four-year sector and under 2 quarters in the 2-year sector. Since we observe earnings over a 60-quarter period, these differences are minor and are unlikely to generate bias in our earnings estimates. For quarters with zero earnings the differences are similarly small. Further, we observe even less variation on the extensive margin: there is little difference in the likelihood of leaving the earnings sample across majors in either sector. This suggests that there is little scope for bias from differential earnings sample attrition across majors.[4]

Table 1 presents descriptive statistics for the analysis samples. Both the two-year and four-year students are positively selected in terms of math and reading scores, and as expected the four-year students score much higher than the two-year students. There is sizable representation among Hispanic, African American, and Asian students. The most prevalent major group is liberal arts, at 22 and 33 percent, respectively, in the four-year and two-year sectors. Biology and health also is popular in both sectors. Majoring in social science, business and economics, communications, or agriculture is much more prevalent in the four-year than in the two-year sector, while two-year students are relatively more likely to major in a vocational area or to be undeclared when they leave school. A very small portion of the sample double

[4] Across many states, Foote and Stange (2022) find that a 10 percentage point difference in the cross-major likelihood of being observed with in-state earnings is associated with an underestimation of major earnings premia by only 1.3%. .Given the low exit rates shown in Table A-2, the bias is likely to be small in our context.

majors. For these students, we code them as majoring in both subjects.

Appendix Table A-3 presents means of the analysis variables by major and sector. There are large differences across majors in terms of incoming math and reading scores, gender, racial/ethnic representation, and earnings. It is likely much of the raw variation in earnings across majors reflects these differences, which highlights the importance of controlling as richly as possible for the composition of students in each major.

b. Measuring Earnings Variability

Our preferred measure of earnings variability is the residualized coefficient of variation (CV), which is the standard deviation of residualized earnings with respect to predicted ($\hat{Y}_{it}$) quarterly earnings divided by mean predicted earnings. This measure quantifies the amount of earnings variability around what individuals are "expected" to earn in each quarter, scaled by mean expected earnings over all observations for the individual. Those with large quarter-to-quarter fluctuations relative to their predicted earnings will have high levels of variability and a larger residualized CV. A negative estimate indicates that a major exhibits lower earnings variability than the base major (liberal arts in our models).

Our preferred approach to constructing the residualized coefficient of variation is to predict earnings using an individual-specific linear function. We decompose the earnings of individual *i* during time *t* (Y_{it}) into an individual-specific intercept at time 0 (α_i), an individual-specific slope with respect to quarters post-high school (β_i), and a residual ($\tilde{Y}_{it}$):

$$Y_{it} = \alpha_i + \beta_i t + \tilde{Y}_{it}. \quad (1)$$

We define $\hat{Y}_{it} = \alpha_i + \beta_i t$ as the predicted earnings in any quarter (t) and $\tilde{Y}_{it}$ is the residual with respect to this linear prediction. Individual-specific intercepts and growth rates are estimated via OLS, using the quarterly earnings data and sample inclusion criteria discussed above. For the intercept, we do not observe earnings at *t=0* because students are enrolled in college during that period. Instead, we estimate the effect of college major on earnings 20 quarters after high school graduation (the first quarter of our earnings data) and project earnings backwards to t=0 using the β_i estimates. Mean α_i and β_i estimates by major are presented in Online Appendix Table A-4.

This approach assumes an individual-specific linear growth profile for earnings. We cannot include a more flexible trend because it is computationally intractable with such a large sample. Appendix Figure A-1 shows that average earnings by time since high school graduation are approximately linear, which helps justify the use of a linear growth parameter. To assess the robustness of our results to more flexible ways of predicting earnings, we use an individual-specific 4-quarter and 8-quarter moving average (MA) ending with the quarter prior to the focal quarter. We use prior quarters to avoid overlap between the data used for prediction and the focal quarter.

Once we have estimated earnings residuals, we calculate the residualized CV as the standard deviation of $\tilde{Y}_{it}$ divided by the mean of $\hat{Y}_{it}$ for each individual using all quarters of included earnings in the sample. We prefer to scale the residualized standard deviation by the mean because there is a mechanically positive relationship between the amount of earnings variability and mean earnings: those who earn more also tend to exhibit higher earnings variance. The residualized CV adjusts for this mechanical relationship, which allows us to examine how major choice influences earnings variability more clearly. We focus on the residualized CV in the main text, but we also show effects on the residualized standard deviation in the appendix. As described below, the residualized standard deviations are what we use to generate earnings shocks in our utility model.

Our analysis of earnings variance aligns with a body of research in labor economics that estimates the empirical relevance of earnings instability (e.g., Gottschalk and Moffitt 1994; Moffitt and Gottschalk 2012; Moffitt and Zhang 2018). These papers typically use annual data, often from the Panel Study of Income Dynamics (PSID), and focus on separating permanent from transitory variance using log earnings residuals. As discussed in Moffitt and Gottschalk (2012), identifying permanent shocks requires a panel that is longer than the one we employ. Further, we are focused on shorter-run variation for which the difference between permanent and transitory shocks is of less interest. We also are unable to use log earnings residuals because of the presence of zero earnings quarters in our data. The residualized standard deviation provides a measure of the volatility of earnings surrounding a local earnings prediction that is calculated separately for each sample member. It is similar to the Window Averaging Method of calculating deviations from average log residuals in an earnings window, which has been shown in prior work to provide an accurate measure of earnings variance over time (Moffitt and Gottschalk 2012).

II. Empirical Methodology

a. Linear Model

To estimate conditional earnings differences across fields, we use a series of linear regression models of the form:

$$Y_{iscjk} = \mu + \boldsymbol{\theta_k}\mathbf{1}(Major_i = k) + \boldsymbol{\Omega X_i} + \delta_{cs} + \gamma_{cj} + \epsilon_{iscjk}, (2)$$

where Y_{iscjk} is an outcome for individual i, from high school s, in high school cohort c, attending postsecondary institution j, and majoring in field k. We estimate models separately by sector (4-year, 2-year). The coefficients of interest in equation (2) are those on each of the aggregated field indicators, $\boldsymbol{\theta_k}$. In all results below, liberal arts is the excluded category, and so the $\boldsymbol{\theta_k}$ estimates are relative to those with a liberal arts major. While we thus compare earnings in each field relative to liberal arts, we note that one can calculate relative returns across any two given fields by comparing the estimates of θ. Since we include non-completers, these parameters capture outcome differences between majors, including those with and without a degree. However, we also examine differences in returns for degree recipients in Appendix Figures A-2 and A-3. All standard errors are clustered at the postsecondary institution-by-high school cohort level, reflecting the correlation of outcomes across students who graduate in the same year and who attend the same college. Results are similar if we cluster by high school.

The $\boldsymbol{\theta_k}$ estimates reflect a causal effect of major choice on earnings under the assumption that the controls and fixed effects in the model are sufficient to account for the non-random sorting of students into majors. This is admittedly a strong assumption, though it is rendered more palatable by the richness of the controls. We control for multiple measures of pre-collegiate academic aptitude: standardized 11$^{\text{th}}$ grade math and reading test scores that one must pass to receive a diploma, indicators for whether a student is in the top decile of each exam distribution within their school, and indicators for whether a student is in the top 10-30 percent of the within-school exam distribution. The distribution indicators are important in this context because of the Texas Top 10 Percent Rule, which grants automatic admission to the top 10% of each high school class to any college in Texas. The actual student rankings used for the Top 10 Percent Rule are based on GPA, which are not included in our administrative data. Andrews, Imberman, and Lovenheim (2020) show that those in the top 30% of these test score distributions are much more likely to be admitted under the top 10% rule. We also control for race and ethnicity indicators (White, non-Hispanic; Black, non-Hispanic; and Hispanic), and indicators for being in a gifted and talented program, being at risk for dropout,[5] and being economically disadvantaged.

The controls are similar to what is used in the most high-quality prior selection-on-observables studies (Altonji, Arcidiacono, and Maurel 2016, Table 8). Our large sample sizes also allow for two types of detailed fixed effects: high school-by-graduating cohort and college-by-cohort, which we refer to as high school and college fixed effects. Because of geographic sorting and patterns of segregation by race/ethnicity and SES, one's high school incorporates a substantial amount of information about socioeconomic background. Furthermore, the sorting of students into different colleges leads to smaller differences in unobservables across students within the same college and cohort than across students in different majors and different institutions. These fixed effects also provide insight into the amount of residual selection remaining when one employs controls that are common in the literature. While we are unable to test the identifying assumption of no selection on unobservables conditional on the included controls, this is a somewhat weaker assumption in our context than in prior research using this method because of our rich control set.

b. Quantile Treatment Effects

To identify the effect of college majors on the cross-sectional distribution of earnings, we estimate unconditional quantile treatment effect models (DiNardo, Fortin, and Lemieux 1996; Firpo 2007). We closely follow the approach used in Andrews, Li, and Lovenheim (2016), who estimate quantile treatment effects of college quality on earnings with similar data. We first take each major pair, where a major pair consists of one of the major groups listed above and liberal arts. Letting k index the non-liberal arts major, we estimate a logit model of the likelihood of majoring in k relative to liberal arts:

$$\Pr(Maj_i = k) = \frac{e^{(\zeta + \mathbf{T}\boldsymbol{X}_i + \omega_{cs} + \phi_{cj} + \nu_{icsj})}}{1 + e^{(\zeta + \mathbf{T}\boldsymbol{X}_i + \omega_{cs} + \phi_{cj} + \nu_{icsj})}} \quad (3)$$

where all other variables are as previously defined. For each non-liberal arts major, we estimate a separate version of equation (3), and the predicted values from these logit models are used to

[5] At-risk status includes students who satisfy at least one of a variety of predictors of dropout behavior, including low achievement, pregnancy or parenthood, interactions with law enforcement, previous drop out, of limited English proficiency, homeless, being previously expelled, or being enrolled in an alternative education program.

construct weights:

$$\psi(x) = \frac{\Pr(\widehat{Maj_\iota} = k)}{1 - \Pr(\widehat{Maj_\iota} = k)}. (4)$$

Equation (4) is the odds ratio of the conditional likelihood of individual i choosing major k (relative to liberal arts), and we apply the weights, $\psi(x)$, to the distribution of earnings among those with a liberal arts major. This generates a counterfactual distribution of earnings that would have been expected if the observed characteristics of students with a liberal arts major were distributed the same as the observed characteristics of those with major *k*. The quantile treatment effect is the vertical difference between the inverse CDFs of the major *k* earnings distribution and the reweighted liberal arts earnings distribution at each quantile.

The assumptions underlying this approach are very similar to the linear selection on observables method. Both methods ultimately are identified from the assumption that the observed characteristics are sufficient to account for the selection of students with different potential earnings into different majors. One subtle difference is that by estimating (3) separately for each non-liberal arts major, we allow the individual controls to have different coefficients for each field. The QTE model estimates the effect of college major *k* relative to liberal arts on the distribution of earnings. It shows how a given major shifts different parts of the earnings distribution relative to the (adjusted) liberal arts earnings distribution. This differs from the distribution of treatment effects, which requires a rank invariance assumption that the treatment does not alter one's rank in the major-specific earnings distribution. This is a stronger assumption that is not possible to test and that we do not invoke. However, the treatment effect on the distribution of earnings is itself important because it is necessary for conducting welfare calculations of treatment effects (Heckman, Smith, and Clements 1997).

III. Results

a. Mean Earnings Effects of College Major and Earnings Trajectories

Panel (a) of Figure 1 presents the estimates of θ_k from equation (2), using observations 16-20 years after completing high school among four-year college students. Since students tend to finish high school in late spring, we start our timeline from the third quarter rather than the first quarter of the calendar year. The black triangles show estimates without controls but with cohort fixed effects, the green squares show the estimates that include the student-level observables shown in Table 1, and the red circles present estimates that also include high school by cohort and college by cohort fixed effects. The red circles represent our preferred estimates, as they control for selection in the most comprehensive way, and the numbers next to each red circle are the point estimates from estimation of equation (2). The point estimates and standard errors are shown in Appendix Table A-5. We use average individual earnings that qualify for sample inclusion and that are in the specified potential experience range to estimate these models. The number of observations in the tables thus reflect the number of individuals rather than the number of quarterly earnings observations. The standard errors tend to be very small relative to the estimates, and in general all of the estimates are statistically significantly different from zero at the 5% level. Thus, we focus our discussion on the point estimates.

Figure 1, panel (a) shows that 16-20 years after college, our preferred model produces large average differences across majors.[6] Engineering and architecture has the highest returns at \$7,901 per quarter relative to liberal arts, with business and economics (\$6,614), biology and health (\$5,655), and IT (\$4,794) also experiencing high relative returns. Average quarterly earnings in this sample are \$16,793, so these effects are large relative to the mean. Since all estimates are positive and statistically significantly different from zero at the 5% level, liberal arts has the lowest mean earnings return followed by social sciences (\$568), communications (\$983), and agriculture (\$1,279).

This figure also shows the importance of our various controls. We note three important patterns with these results. First, control variables matter differentially for different majors. For example, the engineering and architecture estimates are cut almost in half, from \$13,708 to \$7,901, when going from the "no controls" to the most saturated specification. Physical sciences and math, IT, and agriculture estimates also are substantively attenuated by the controls. The estimates for social sciences, vocational, and communications are much less sensitive to the controls included in the model. This pattern of results suggests differential selection on observables across majors. Second, the controls universally (weakly) attenuate the estimates.

[6] Figures 1 and 2 do not show the estimates for "undeclared," since this is a difficult major to interpret because all undeclared majors drop out of college before obtaining a degree. This group is included when we estimate equation (2), and results for this "major" are shown in Online Appendix Tables A-5 and A-6.

Third, the high school-cohort and college-cohort fixed effects have a sizable impact on the estimated returns for several of the majors, over and above the observables in the "controls" model. These patterns highlight the importance of including these fixed effects in selection on observable models of returns to college major.

Panel (b) of Figure 1 shows estimates for ranges of potential experience using our preferred specification. Online Appendix Table A-5 reports the associated coefficients and standard errors, along with estimates using different control sets for each experience range. Figures analogous to Panel (a) of Figure 1 for years 6-10 and 11-15 after high school are shown in Online Appendix Figure A-4. Several fields exhibit substantial growth in returns over time: biology and health returns increase from $413 to $5,655 in the two decades after high school, engineering and architecture increases from $3,521 to $7,901, physical sciences and math increases from $666 to $3,374, and business and economics increases from $2,418 to $6,614, all relative to liberal arts. It is possible that some of this growth reflects investments in graduate school and subsequent sorting of these students into high-paying professions.[7]

The return to each major increases relative to liberal arts over time, although the rate of increase is lower for agriculture, communications, and social sciences. Liberal arts thus is the lowest earning field up to twenty years after high school, and its position relative to other majors worsens as students gain labor market experience. The over time shows that the point in one's career at which earnings are observed matters for accurately measuring the returns to different majors, relative to liberal arts and to one another. The changes we document are not simply a reflection of a common proportional shift: biology and health returns increase by a factor of 12.7 across time periods,[8] while physical sciences and math, agriculture, and communications all increase by over a factor of 4. IT shows the lowest proportional growth, at just under 100%, and the remainder of the majors experience relative increases of 100-200% over time. Different relative growth across fields also causes some rank switching as workers gain experience.

It is worth briefly considering how our results compare to other estimates in the literature. The most comprehensive analysis of returns to field of study is Kirkebøen, Leuven and Mogstad

[7] See Altonji and Zhong (2021) and Altonji and Zhu (2021) for estimates of the returns to graduate school. Altonji and Zhu (2021) study a similar set of students and cohorts in Texas. Lovenheim and Smith (2023) review the returns to graduate school literature.

[8] It is likely a substantial part of the pattern for biology and health is due to low salaries immediately after medical school, which then rise quickly after individuals complete their medical residencies.

(2016), who use a regression discontinuity approach to examine the returns to college major in Norway measured 8 years after application. This roughly equates to our 6 to 10 year estimates. In general, their estimated returns to each major relative to humanities are much higher than in our setting. For example, the return to business is over $12,000 per quarter and the return to engineering is almost $15,000 per quarter. Applying the growth rates from our results suggests that by 16 to 20 years post-application the quarterly return to engineering or business versus humanities will grow to approximately $34,000. Hence, the longer-run average returns in Kirkebøen, Leuven and Mogstad (2016) are quite large relative to our estimates. Nonetheless, the rank orderings in their study generally align with our results. We emphasize, however, that applying our results to the Norwegian setting requires strong assumptions.[9]

In a paper that is a closer setting to ours, but more narrowly focused, Bleemer and Mehta (2022) use a regression discontinuity design to estimate the return to majoring in Economics relative to students' second-choice majors at UC-Santa Cruz among students who are 4 to 9 years post-high school. They find a return of about $5,500 per quarter, which is over double our estimate from Figure 1 of $2,418. This difference could reflect marginal vs. average returns, or it could be that the returns to economics at UC-Santa Cruz are particularly high.

Our growth patterns align with those of Choi et. al (2023), who find that engineering, business, and computer science majors experience faster earnings growth than humanities majors using matched ACS and Longitudinal Employer-Household Dynamics data. Additionally, Heinesen et. al. (2022) show high correlations (0.80 to 0.86) between short- and medium-run earnings payoffs of majors in Norway and Denmark and that earnings patterns between the two countries converge over longer time periods. The time profiles documented by us and others suggest that scholars may see heterogeneity in findings across papers based only on the experience composition of the sample.

Figure 1 and the prior research discussed above focus on the four-year sector. We now present new evidence on these returns in the two year sector in Figure 2, with coefficients and standard errors shown in Appendix Table A-6. Similar heterogeneity is evident as in the four-

[9] Of particular importance is that in Norway, students can choose law or medicine as a major while in the US many students major in a liberal arts field and later go into law (and to a lesser extent, medicine). Thus, in our data, the liberal arts fields we use as the baseline includes these high earning individuals, compressing the returns distribution.

year sector, although the specific patterns across majors differ and the gaps are smaller. This highlights the value of examining the two levels separately. In panel (a), sixteen to twenty years after high school the highest earnings are found among vocational ($1,065) and biology and health ($1.027) majors, relative to liberal arts majors. Communications, education, social sciences, and IT all exhibit negative relative returns, with the penalty for communications being particularly large at -$1,247. Average quarterly earnings among 2-year students equals $11,628 sixteen to twenty years after high school, so these effects are sizable when compared to the mean. Estimates for earlier years are presented in Online Appendix Table A-6 and Figure A-5.

Panel (a) of Figure 2 again shows the importance of the controls we use to account for selection of students with different potential earnings into different majors. Unlike in the four-year sector, including controls does not always move the estimates in the same direction. For example, for vocational, agriculture, IT, engineering, and physical sciences, including the full set of controls leads to decreases in the relative returns. This is evidence of positive selection into these majors relative to liberal arts. The opposite is true for education, biology and health, and social sciences, for which the relative returns increase (or become less negative) after controls are included. As with the results for four-year students, the high school by cohort and college by cohort controls have a sizable but differential effect on the estimates.

The relative earnings associated with different majors changes with potential experience, as demonstrated in panel (b), though lifecycle changes are much more muted than in the four-year sector Relative to liberal arts, the returns for vocational and agriculture are high in the first two periods after high school and then diminish somewhat over the final period. The positive return to vocational degrees aligns with prior literature showing that high average returns to vocational two-year degrees (Lovenheim and Smith 2023), particularly in the short run. Relative earnings growth is strongest for physical science and math majors, with business and economic and engineering and architecture exhibiting quite modest growth over time. The relative returns to biology and health change little, in contrast to the 4-year sector, and communications, social sciences, education and IT majors all experience declines in earnings over time relative to liberal arts. Especially because the direction of the changes varies by major, these estimates do not simply reflect a common proportional shift from different baselines: communications returns decline by a factor of 3, education returns decline by a factor of 36, and IT returns decline by a factor of 15.5. In contrast, physical science and math returns increase by over 200%, and vocational, engineering and architecture, and business and economics increase by between 16 and 40%. Biology and health returns increase by only 4% across periods.

The patterns we document are not driven by differences in the likelihood of graduating across fields. One might worry that many non-completers would be denoted as "liberal arts" if they were, by default, registered in colleges' liberal arts program upon initial enrollment, conflating earnings estimates. Appendix Figures A-2 and A-3 contrast our main estimates to those where the sample is restricted to only degree recipients. While the magnitudes of the major differentials are often greater when examining only degree recipients – particularly for vocational, biology and health, and engineering and architecture fields in 2-year institutions – the relative ordering of fields is quite similar to our preferred sample that also includes non-completers. Furthermore, these figures demonstrate the importance of labor market experience, since the completer estimates often are smaller in earlier periods and then grow over time.

b. Across-worker Variation in Returns

The mean earnings impact of major choice may be a poor reflection of earnings for the typical student in a field. A major with high mean earnings can reflect few workers having very high earnings with most workers having lower earnings, or it can reflect most workers experiencing modestly high earnings. Thus, the mean may contain significant ex-ante risk in terms of the likelihood a randomly chosen student obtains that level of earnings. If mean earnings returns come with substantial risk, this reduces the benefits of specific majors, especially if students are risk averse. No research has examined this question with respect to college majors.[10] While we discuss this form of variation as ex-ante risk, other interpretations are also possible. Heterogeneity in the effect of college major choice across individuals that is known ex-ante when choices are made is not a component of risk that reduces welfare. We are not aware of evidence on how much students know about and make choices based on their individual-specific returns to college major. Thus, our welfare analysis in section IV considers models both with and without including across-worker variability as a source of risk.

We estimate quantile treatment effects (QTE) of each major relative to liberal arts. These

[10] To our knowledge, the only analyses of distributional effects of majors are Schanzenbach, Nunn, and Nantz (2017) and Leighton and Speer (2020), who investigate differences in major-specific earnings across occupations.

estimates show how each major shifts the entire distribution of earnings, which provides insight into which workers experience the largest relative returns and the resulting variation across workers in average returns. Figure 3 shows these estimates for four-year students. The outcome is average person-level mean quarterly earnings across all years and experience levels included in our sample. The solid curve in each panel presents the QTE estimates, and the shaded region shows the 95% confidence interval that is calculated using a block bootstrap at the institution-by-major level.

The mean differences across fields do a poor job of capturing the earnings consequences of major choice. The slope of the QTE curves vary considerably across majors. Engineering & architecture, business & economics, and IT, all exhibit strongly upward sloping QTEs across the entire earnings distribution. This means that these have disproportionately higher earnings premia for high-earning individuals. Nonetheless, while the returns are inequitable, even at the bottom of the distribution, none of the estimates are negative, and so these majors generate higher earnings than liberal arts throughout the distribution. As such, the mean effect does not characterize the effect on the distribution of earnings, however the risk students face in choosing these majors is mitigated by the positive effects across the earnings distribution.

The ex-ante risk associated with choosing some majors is potentially much higher than liberal arts, as the returns to these majors largely flow to those at the top of the earnings distribution. For agriculture, biology and health, and physical science and math, earnings effects are predominantly localized to the top of the earnings distribution, with positive but small impacts below the 70th percentile. The relative returns to social science, vocational, and communications stem solely from the very top of the distribution. Business and economics shows substantial gains below the 70th percentile but the relative returns accelerate as one enters the upper part of the distribution. Hence, the modest positive average returns are driven almost entirely by higher earners. Most students in these majors experience no or very small returns relative to liberal arts. The QTE estimates are actually *negative* and significant, though small, for half of the social science distribution. Mean effects thus present a misleading picture of the earnings returns to these majors.

Figure 4 presents QTE estimates for 2-year students. The patterns across majors differ from those in the four-year sector, but the main takeaway that the mean masks important distributional effects remains. The QTEs are strongly negatively sloped for communication, social science, and education majors. This means that the earnings penalties associated with these majors relative to liberal arts are particularly large at the top of the earnings distribution. The QTEs are relatively flat among business & economics, IT, and physical science and math. For these majors, the average estimates are representative of what students can expect to earn. Vocational, biology and health, and engineering and architecture majors exhibit positive gradients like we see for many four-year fields, where the benefits of the major accrue disproportionately to the highest earners. The differences in the QTE estimates across sectors and majors suggests that mean effects should be interpreted carefully, as even similar mean estimates are likely to mask different distributional effects that could reflect ex-ante risk for students.

c. Within-person Earnings Variability

Prior work has not addressed the potential for major choice to generate variation in earnings within individuals on a quarterly (or annual) basis. Such fluctuations in earnings can be harmful to families if they lack full access to credit, especially if their average earnings are low or if they come from disadvantaged backgrounds and lack "buffer stock" savings. If individuals are risk-averse or credit constrained, such variation can reduce their well-being. To examine whether certain majors are associated with unexpected low or high earnings periods within or across years, we estimate equation (2) using the residualized coefficient of variation (CV) measure described in Section II.b.

Table 2 presents estimates that vary with respect to the controls used, the earnings prediction model, and the frequency of the earnings observations. Columns (1) and (2) use our preferred individual linear prediction model for earnings, with column (2) containing the main estimates that include all controls. The point estimates in column (2) vary in sign, suggesting that some majors exhibit more variability than liberal arts and some less. The positive estimates for agriculture, communications, biology and health, physical sciences and math, and social sciences range from 0.007 to 0.047, however only the estimates for biology & health and social sciences are statistically different from zero at the 5% level. These positive estimates are modest in magnitude, indicating that these majors increase quarterly variability by about 6% relative to the mean SD. Estimates for communications, IT, vocational, engineering & architecture, and business & economics are negative and range from -0.002 to -0.088. All but the communications estimates are significant at the 5% level and are slightly larger in absolute value than the positive coefficients. Comparing the results across columns also shows that the effects are not very sensitive to the inclusion of controls.

The subsequent columns of Table 2 show that the main patterns are robust to alternative modeling assumptions. Using a 4- or 8-quarter moving average to predict earnings (columns (3) and (4), respectively) generates similar patterns albeit with smaller magnitudes because the prediction model is more flexible. Effects are similar in proportion to the mean. Our estimates also are robust to dropping the final four quarters of earnings (column 5) to account for possible measurement error from our exclusion of quarters at the end of the sample that ought to be included as zeros. Finally, in column (6), we estimate models using annual earnings rather than quarterly earnings to smooth out seasonality that may be predictable to workers and thus not a form of volatility as typically understood. Interestingly, the estimates change little, indicating that the higher-frequency data do not exhibit more evidence of earnings variability across majors. This is consistent, however, with the modest effects we find in Table 2; in general, there is not much systematic difference in earnings variability across majors in the four-year sector. While modest, the pattern of estimates is positively correlated with the mean effects: the correlation between the residualized SD estimates and the 16 to 20 year mean estimates across fields is -0.48. Hence, high-earning majors are even more attractive because they exhibit lower levels of within-person variability in earnings as well.[11]

The effects of college major on the coefficient of variation among 2-year students are shown in Table 3. The estimates in column (2) are similar in magnitude to their counterparts in the four-year sector, ranging from -0.068 (vocational) to 0.046 (physical sciences and math), or -8.5% to 5.8% of the mean SD. Six of the estimates are significant at the 5% level. Only 3 of the estimates are positive, and of these only the physical sciences and math estimate is statistically significant. Hence, in the two-year sector, there is a similar level of earnings variability for majors relative to liberal arts as in the four-year sector, but the specific pattern across majors differs somewhat. Also, the estimates are similar when we use the 4-quarter and 8-quarter

[11] Online Appendix Table A-7 shows estimates of the effect of major choice on the residualized standard deviation. When scaled by mean earnings, majors vary with respect to liberal arts in terms of whether they exhibit more or less within-worker variability, but they all exhibit more absolute variability relative to liberal arts that is driven in part by the mechanical positive relationship between mean earnings and earnings variance.

moving averages and do not substantively change when we exclude the final four quarters of earnings or use annual earnings. Like in the four-year sector, the residualized SD estimates are negatively correlated with the 16 to 20 year mean returns, with a correlation coefficient of -0.20. Higher-earning fields have more stable earnings. Prior research thus has understated the difference across fields by ignoring this dimension of earnings returns.[12]

IV. Implications and Lifecycle Returns

The results in Section III show evidence that the return to college major choice varies with potential experience, exhibits substantial cross-sectional variation, and has some implications for within-worker earnings variability over time. We use our estimates to simulate a lifecycle utility model to assess how utility returns relate to earnings returns and document the role of risk aversion in driving the relative returns to college majors.

Following the framework of Dillon (2018), we assume workers maximize intertemporal utility with constant relative risk aversion:

$$\max_{C_{it}} \sum_{s=t}^{L} \beta^{s=t} \frac{C_{is}^{1-\gamma}}{1-\gamma} \text{ s.t. } A_{it+1} = (1+\mathrm{r})\,(A_{it} + Y_{it} - C_{it}). \qquad (5)$$

Where C is consumption, A is assets, Y is earnings, r is the interest rate, β is the discount rate, and γ is the coefficient of relative risk aversion. We simulate the entire earnings path for 200 individuals for each major using the parameters estimated above and then compute lifecycle utility under different assumptions about savings behavior and uncertainty. To do this, we first take a draw from the distribution of QTE estimates of average quarterly earnings, reported in Figures 3 and 4. We use a distribution of QTE estimates for each field at each decile from the 10^{th} percentile to the 90^{th} percentile with equal (uniform) probability. This gives each hypothetical person an average quarterly earnings in a given major and an average quarterly earnings in Liberal Arts for comparison. We next assign a major-specific growth rate, which is the same for everyone in a given major and is taken from columns (4) and (8) of Table A-4. From the growth rate and average earnings, we back out initial period earnings. That is, we calculate the time intercept that would be generated by the average earnings effect at the

[12] Online Appendix Table A-8 shows effects on the residualized SD. The estimates vary in sign, with negative estimates for communications, IT, social sciences, and education, all of which are statistically significantly different from zero. There is somewhat less residual variation in earnings in the two-year sector than in the four-year sector, which is expected given the lower level of earnings among two-year students.

assigned quantile and the major-specific growth rate. Note that this effectively models the QTE variation as a level shift rather than a growth shift; growth rates are assumed to be equal across quantiles within each major.

Using the intercept and growth rates, we predict quarterly earnings using a linear projection over time by major. To incorporate within-worker variability, we generate a realization of earnings using a normal distribution with a mean equal to predicted earnings and a standard deviation equal to the residualized standard deviation estimates in column (2) of Tables A-7 and A-8. This effectively assumes that workers are hit by quarterly shocks that are normally distributed with mean zero and have a standard deviation equal to the residualized SD estimate. Any negative earnings estimates are set to zero. We assume that these shocks are unexpected, while earnings growth due to potential experience is expected. Another way to conceptualize our approach is in terms of persistent versus transitory income shocks (e.g., Blundell, Pistaferri, and Preston 2008). Earnings growth over time represents persistent income shocks that continue to be incorporated into earnings, while the shocks are transitory in nature and only affect earnings for the given quarter.

We do not observe savings or assets and hence cannot estimate savings parameters. Thus, in the simulations we consider three savings scenarios and the extent to which income shocks are unexpected/transitory in order to bound the range of potential effects:

(1) *Uncertainty, No Savings*: we calculate utility in each quarter assuming C = Y, where earnings in each quarter are calculated using the simulated earnings described above. The model reflects utility differences arising from earnings growth and transitory shocks.

(2) *Certainty, No Savings*: we assume that C equals predicted earnings with no transitory shocks. The only source of earnings variation for an individual comes from earnings growth over time. The difference between this model and (1) isolates the utility costs of transitory variability in a model when savings are not permitted.

(3) *Permanent Income Hypothesis (PIH)*: The permanent income hypothesis states that with perfect credit markets as long as earnings shocks are expected consumption will be perfectly smoothed across quarters. We thus calculate the present value of the income stream and split it evenly (adjusting for time discounting) across quarters. This model allows for certainty with savings and borrowing permitted to offset transitory shocks.

Two important parameters in equation (5) are the discount rate, β, and the coefficient of relative risk aversion (CRRA), γ. Our base specification assumes a quarterly discount rate of 0.99, which translates to an annual discount rate of 0.96. We use a CRRA of 3 in our preferred results, and we then show how our results change when we use risk aversion parameters of 0.75, 1.5, and 2.

We first use the *Uncertainty, No Savings* as the baseline model and examine how mean earnings returns 16 to 20 years post-HS compare to utility returns. These comparisons are shown in Figure 5, separately for 2-year and 4-year students. In the 4-year sector in panel (a), mean earnings effects tracks utility closely – the correlation between estimates is 0.7 – with some notable deviations: IT and agriculture have larger relative utility returns than earnings returns, while biology and health have lower utility returns compared to earnings since early-career earnings are low and grow substantially over time. Even with a 0.96 discount rate, the low early career earnings put downward pressure on lifetime utility. Similarly, IT has a higher utility returns because early-career earnings returns are high and remain so over time. In general, the 16 to 20-year returns align well with the utility returns, but there are some differences that highlight the value of considering other moments of earnings within a utility framework.

When we reduce the coefficient of relative risk aversion to 0.75, as shown in Appendix Figure A-6, Panel (a), earnings returns become more correlated with lifecycle returns, with the Pearson correlation coefficient increasing to 0.8. However, the basic patterns remain stable. Only physical sciences and math, vocational, and communications switch positions relative to the best fit line, but none of the changes are large. Nonetheless, the key takeaway from these results is that utility tends to be larger for fields with high mean earnings returns, regardless of the level of risk aversion. This indicates that the mean returns 16-20 years post-HS are a very useful – perhaps the most useful – statistic when evaluating the labor market returns to major choice. It is important to note that this result is not immediately obvious when considering risk profiles of different fields, and so our model supports the existing emphasis on mean returns in the literature and public policy. However, our results also show that mean effects alone do not fully characterize the returns to college major choice.

Panel (b) of Figure 5 shows results for the 2-year sector. Once again there is a strong positive correlation between average earnings returns and utility (corr coefficient = 0.7). It is notable that there is a clear separation between fields – communications, education, and social sciences make a low-utility, low-earnings group while the rest (including liberal arts) form a high utility, high earnings grouping. The broad pattern is similar to 4-year institutions. Biology and health and physical sciences and math have much higher utility than earnings returns, while engineering and architecture, business and economics, and vocational are high in both. Agriculture and IT exhibit higher utility returns relative to earnings. Panel (b) of Appendix Figure A-6 shows that there is little change when we decrease the CRRA to 0.75 for 2-year institutions. Thus, the level of risk aversion plays a smaller role in the interpretation of earnings returns in the two-year than in the four-year sector. Like in the four-year sector, a central conclusion drawn from these results is that mean earnings in one's mid-30s do a good job of characterizing the returns to college major choice.

Figures 6 and 7 examine the role of risk along two dimensions for the four- and two-year sectors, respectively. Each panel shows estimates that vary the coefficient of relative risk aversion from of 0.75 to 3, which highlights the role of risk preferences in driving the utility returns to college major. Second, the two panels show how utility effects differ when we incorporate across-worker variability captured by the QTE estimates (panel a) versus giving each worker in each major the mean intercept (panel b). Varying the use of quantiles isolates the role of ex-ante risk, and varying the CRRA and ex-ante risk together shows how risk preferences and risk from cross-sectional earnings variation intersect.

Estimates for 4-year students are shown in Figure 6 and illustrate the importance of the risk aversion parameter used in the model. Using the quantile estimates in panel (a), the relative returns to all majors outside of social science get larger relative to liberal arts as the risk aversion parameter increases. Regardless of the risk-aversion parameter, engineering and architecture, IT, and business and economics are the highest return majors. Thus, while changing γ does not tend to alter the ranking of majors, it has a substantial effect on the magnitude of the utility returns. This is the first evidence in the literature showing that student risk aversion is an important parameter in driving the private returns to college major.

Comparing across panels (a) and (b) allows us to examine the role of ex-ante risk in utility returns to major choice. In general, while magnitudes change, there is little difference in the rank ordering of majors, indicating that ex-ante risk is not a particularly important input into utility gains from major choice in the four-year sector. There are a couple of exceptions, however. Social sciences is sensitive to the use of QTE estimates, especially when students are risk averse. This sensitivity occurs because the high QTE effects at the top of the social science distribution help protect some students from transitory earnings shocks, which becomes more valuable when they are more risk averse. There is a similar, albeit less dramatic, change for agriculture for the same reason.

Figure 7 shows results for 2-year institutions. In Panel (a), for majors outside of physical sciences and math, we see a familiar pattern that increasing risk aversion leads to larger differences in returns relative to liberal arts: the lifecycle utility returns are heavily influenced by the extent of risk aversion. In some cases, increasing γ leads to more negative relative returns (e.g., communications, education, and social sciences), while for others it makes the relative returns larger (e.g., agriculture, engineering & architecture, and vocational). Only for physical sciences and math is there little effect of the CRRA on lifecycle utility returns.

Comparing panels (a) and (b), the pattern of returns by CRRA differs for biology and health, communications, social science, and education in ways that help to illustrate the important role of ex-ante risk and risk preferences, which is considerably larger in the 2-year sector than in the 4-year sector. In panel (a), increasing risk aversion makes relative returns more negative for biology and health, while it has the opposite effect in panel (b) that does not use the QTE-based intercepts. This difference is driven by the large value of α (Appendix Table A-4) and the fact the QTE curve is flat below the 60^{th} percentile. Biology and health majors experience a large amount of earnings variability (Table A-8), which when interacted with ex-ante risk lowers the returns for more risk-averse students. The large intercept for biology and health in panel (b), in contrast, produces more certainty for students that is of higher value when they are more risk averse.

The pattern of results for communications, education, and social science can be explained by the downward sloping QTE estimates for these majors combined with the negative residualized SD estimates in Table A-8. With a common intercept in panel (b), these majors are relatively more attractive when risk aversion increases because they exhibit lower levels of residual earnings variance. However, the ex-ante risk that leads to much lower earnings at the top of the distribution is sufficiently large to undo or reverse this effect for these majors.

Taken together, the results from Figures 6 and 7 demonstrate the importance of risk and risk aversion. The higher earnings of each major relative to liberal arts and the upward sloping QTE curves in the four-year sector protect students from within-worker earnings variance, leading these majors to become even more attractive from a lifecycle utility perspective when risk aversion is higher. In the two-year sector, the results are more mixed and depend on the shape of the QTE curve as well as the direction of the residual standard deviation effect.[13]

Finally, we examine the role of savings and within-worker variation in earnings in Online Appendix Figure A-7 by showing simulated returns to majors under the three different modeling assumptions discussed above using a CRRA of 3. The figure exhibits some differences across models in relative utility, typically in the range of 0.15 to 0.2. This variation is modest in relation to the baseline estimates, suggesting that the specific model we use does not drive the results. Comparing the non-savings returns under certainty to those under uncertainty, the results indicate that transitory earnings variation plays a role in driving the benefits to certain majors, but not usually enough to affect the rank-ordering of majors. Notably, for 4-year students, uncertainty increases utility for most fields relative to liberal arts. This implies that the returns to liberal arts are particularly sensitive to including earnings volatility in the model, which is not surprising given the low average earnings of liberal arts majors. These results reinforce those from Figures 6 and 7 in showing that earnings variance affects the utility returns to college major choice when students are risk averse.

V. Conclusion

We fill several gaps in our knowledge of how major choice in college affects subsequent labor market outcomes, using administrative data from Texas that allows us to link all public K-12 students in the state with their public higher education and quarterly earnings records. These data provide us with a sample size and a rich set of covariates that are unique in the returns to major literature using selection on observables techniques. We use these data to estimate how college major choice affects earnings trajectories, cross-worker variation in average earnings, and within-worker variance in earnings. We then embed our estimates in a lifecycle utility model that highlights the role of risk and risk preferences in determining the returns to field choice in both the 4-year and 2-year college sectors.

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[13] In results available upon request, we show that the estimates are not sensitive to the discount rate used for any level of γ.

Our paper makes several contributions. First, we show that there is wide variation in mean earnings returns that vary with worker experience. In some cases, the rank order of majors changes over time, and majors that initially appear as low-return become higher-return majors later in one's career. This is important information for measuring lifetime returns, and it also suggests that studies using workers of different ages will produce different results.

Second, we move beyond mean returns to estimate two forms of earnings variation. We first estimate quantile treatment effects of college major on earnings. We find that there is substantial heterogeneity across majors in how they affect the earnings distribution and that among both 2-year and 4-year students the mean returns to college major do a poor job of characterizing distributional effects. Most majors have different effects on the upper relative to the lower part of the earnings distribution – in some cases with disproportionately higher returns to the top 30% of the distribution – which emphasizes that mean effects contain sizable ex-ante risk for students. We also present new evidence on how field of study affects within-worker variation in earnings and find that, relative to each major's mean, differences in this variation across majors are modest.

Finally, we use these estimates to simulate a CRRA lifecycle utility model under various assumptions about savings and risk aversion. We find that mean earnings 16 to 20 years after high school are strongly positively correlated with simulated utility returns, but there are some differences driven by the trajectory of earnings and various dimensions of risk. Utility simulations highlight the important role of risk preferences and earnings variance in driving the returns to college major, which has not been shown in prior studies. In the four-year sector, higher levels of risk aversion lead to increased returns from most fields relative to liberal arts because of higher mean levels of earnings that are sufficiently large to protect against earnings variance. In the two-year sector, mean earnings differences across majors are smaller but still positively correlated with utility and the effect of higher risk aversion is more mixed across majors. The specific patterns are determined by the shape of the quantile treatment effect estimates and the sign of within-worker earnings variance effects, which highlight the complex interactions between risk preferences and earnings variance in this setting. These results highlight the importance of earnings risk and risk preferences in estimating the returns to college major choice.

Taken together, our results show the value of moving beyond mean earnings effects at a given age to better understand how college major choice affects labor market outcomes. We have focused on gross returns throughout because we lack data on costs of these programs. Costs can vary considerably across different fields of study (Altonji and Zimmerman, 2018; Hemelt et. al. 2021), and in some cases tuition varies across fields as well (Stange, 2015; Andrews and Stange, 2019). Estimating net private and social returns is an important direction for future work. Distributional effects also are more difficult to communicate in a salient way to prospective students. Wiswall and Zafar (2015, 2021) and Patnaik et al. (2022) show that students' major choices are responsive to information on mean returns and other potential non-earnings returns. A question worthy of future study is whether they also respond to information about how majors affect the trajectory of earnings as well as the cross- and within-worker variance in earnings.

References

Altonji, Joseph G., Peter Arcidiacono, and Arnaud Maurel. 2016. "Chapter 7 - The Analysis of Field Choice in College and Graduate School: Determinants and Wage Effects," in E. Hanushek, S. Machin, and L.Woessmann, eds., Handbook of the Economics of Education, Vol. 5, Elsevier: 305 – 396.

Altonji, Joseph G., Erica Blom, and Costas Meghir. 2012. "Heterogeneity in Human Capital Investments: High School Curriculum, College major, and Careers." NBER Working Paper No 17985.

Altonji, Joseph G. and Ling Zhong, 2021. "The Labor Market Returns to Advanced Degrees." *Journal of Labor Economics* 39(2): 303-360.

Altonji, Joseph G. and Zhengren Zhu, 2021. "Returns to Specific Graduate Degrees: Estimates using Texas Administrative Records." Unpublished working paper.

Altonji, Joseph and Seth Zimmerman 2018. The Costs of and Net Returns to College Major. In C. Hoxby and K. Stange eds., *Productivity in Higher Education*, forthcoming, Chicago, Illinois: University of Chicago Press.

Andrews, Rodney J., Scott A. Imberman and Michael F. Lovenheim. 2017. "Risky Business? The Effect of Majoring in Business on Earnings and Educational Attainment." NBER Working Paper No. 23575.

Andrews, Rodney J., Scott A. Imberman, and Michael F. Lovenheim. 2020. "Recruiting and Supporting Low-income, High-achieving Students at Flagship Universities." *Economics of Education Review* 74: 101923.

Andrews, Rodney, Jing Li, and Michael Lovenheim, 2016. "Quantile Treatment Effects of College Quality on Earnings. *Journal of Human Resources*, 51(1): 201-238.

Andrews, Rodney and Kevin Stange, 2019. "Price Deregulation and Equality of Opportunity in Higher Education: Evidence from Texas. *American Economic Journal: Economic Policy* 11(4): 31-65.

Anelli, M, 2018. The Labor Market Determinants of the Payoffs to University Field of Study. Unpublished working paper. February 15, 2018.

Arcidiacono, Peter. 2004. "Ability Sorting and the Returns to College Major." *Journal of Econometrics* 121(1): 343-375.

Autor, David H. 2014. "Skills, Education, and the Rise of Earnings Inequality among the" Other 99 Percent." *Science* 344(6186): 843-851.

Bleemer, Zachary and Aashish Mehta. 2022. "Will Studying Economics Make you Rich? A Regression Discontinuity Analysis of the Returns to College Major." *American Economic Journal: Applied Economics* 14(2): 1-22.

Blundell, Richard, Luigi Pistaferri, and Ian Preston. 2008. "Consumption Inequality and Partial Insurance." *American Economic Review* 98(5): 1887-1921.

Bound, John, and Sarah Turner. 2011. "Dropouts and Diplomas: The Divergence in Collegiate Outcomes," in E. Hanushek, S. Machin, and L.Woessmann, eds., <u>Handbook of the Economics of Education, Vol.4</u>, Elsevier: 573 – 613.

Bound, John, Michael F. Lovenheim, and Sarah Turner, 2010. "Why Have College Completion Rates Declined? An Analysis of Changing Student Preparation and Collegiate Resources." *American Economic Journal: Applied Economics* 2(3): 129-57.

Britton, Jack, Laura van der Erve, Chris Belfield, Anna Vignoles, Matt Dickson, Yu Zhu, Ian Walker, Lorraine Dearden, Luke Sibieta, and Franz Buscha. 2021. "How Much Does Degree Choice Matter?" IFS Working Paper W21/24.

Carnevale, Anthony P. and Ben Cheah. 2013. "Hard Times: College Majors, Unemployment and Earnings." Center on Education in the Workforce Report, Georgetown University.

Carnevale, Anthony P., Ben Cheah and Andrew R. Hansen. 2015. "The Economic Value of College Majors." Center on Education in the Workforce Report, Georgetown University.

Choi, Woosuk, Josh Kinsler, Alexis Orellana, and Ronni Pavan. 2023. "College Majors and Earnings Growth." Working Paper.

Christiansen, Charlotte, Juanna Schröter Joensen, Helena Skyt Nielsen. 2007. "The risk-return trade-off in human capital investment." *Labour Economics* 14 (6): 971-986.

Delaney, Judith M. and Paul J. Devereux. 2019. "More Education, Less Volatility? The Effect of Education on Earnings Volatility over the Life Cycle." *Journal of Labor Economics* 37(1): 101-137.

Deming, David J. 2017. "The Growing Importance of Social Skills in the Labor Market." *Quarterly Journal of Economics* 132(4): 1593-1640.

Deming, David J. and Kadeem Noray. 2020. "Earnings Dynamics, Changing Job Skills, and STEM Careers." *Quarterly Journal of Economics* 135(4): 1965-2005.

Denning, Jeffrey T., Eric Eide, Kevin Mumford, Richard W. Patterson, and Merrill Warnick, Forthcoming. “Why Have College Completion Rates Increased? An Analysis of Rising Grades.” *American Economic Journal: Applied Economics*.

Dillon, Eleanor. 2018. “Risk and Return Tradeoffs in Lifetime Earnings,” *Journal of Labor Economics* 36(4), pp. 981-1021.

DiNardo, John, Nicole M. Fortin, and Thomas Lemieux, 1996. “Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach.” *Econometrica* 64(5): 1001-1044.

Firpo, Sergio, 2007. “Efficient Semiparametric Estimation of Quantile Treatment Effects.” *Econometrica* 75(1): 259-276.

Foote, Andrew and Kevin Stange. 2022. “Migration from Administrative Data: Problems and Solutions with an Application to Postsecondary Education.” NBER Working Paper 30232.

Gottschalk, Peter, and Robert Moffitt. 1994. “The Growth of Earnings Instability in the U.S. Labor Market.” *Brookings Papers on Economic Activity* 1994(2): 217-272.

Hastings, J.S., C.A. Neilson, and S.D. Zimmerman, 2013. “Are Some Degrees Worth More Than Others? Evidence from College Admissions Cutoffs in Chile,” NBER Working Paper No. 19241.

Hamermesh, Daniel S. and Stephen G. Donald, 2008. “The Effect of College Curriculum on Earnings: An Affinity Identifier for Non-ignorable Non-response Bias.” *Journal of Econometrics* 144(2): 479-491.

Heckman, James J., Jeffrey Smith, and Nancy Clements, 1997. “Making the Most out of Programme Evaluations and Social Experiments: Accounting for Heterogeneity in Programme Impacts.” *Review of Economic Studies* 64(4): 487-535.

Hemelt, Steve, Fernando Furquim, Andrew Simon, John Sawyer, and Kevin Stange. 2021. “Why is Math Cheaper than English? Understanding Cost Differences in Higher Education.” *Journal of Labor Economics* 39(2): 397-435.

Hemelt, Steven, Brad Hershbein, Shawn Martin, and Kevin Stange, 2021. “The Skill Content of College Majors: Evidence from the Universe of Online Job Ads.” NBER Working Paper No. 29605.

Hershbein, Brad and Melissa Kearney, 2014. “Major Decisions: What Graduates Earn Over Their Lifetimes.” *Hamilton Project Report.*

Hershbein, Brad, Benjamin Harris, and Melissa Kearney, 2014. “Major Decisions: Graduates’ Earnings Growth and Debt Repayment.” *Hamilton Project Report.*

James, Estelle, Nabeel Alsalam, Joseph C. Conaty, and Duc-Le To. 1989. “College Quality and Future Earnings: Where Should You Send Your Child to College?” *American Economic Review* 79(2): 247-252.

Jepsen, Christopher, Kenneth Troske, and Paul Coomes. 2014. “The Labor-market Returns to Community College Degrees, Diplomas, and Certificates.” *Journal of Labor*

Economics 32(1): 95-121.

Kane, Thomas J. and Cecilia Elena Rouse, 1995. "Labor-Market Returns to Two-and Four-Year College." *American Economic Review* 85(3): 600-614.

Kim, Chang Hwan, Christopher R. Tamborini, and Arthur Sakamoto. 2015. "Field of Study in College and Lifetime Earnings in the United States." *Sociology of Education* 88(4): 320-339.

Kinsler, Josh and Ronni Pavan, 2015. "The Specificity of General Human Capital: Evidence from College Major Choice." *Journal of Labor Economics* 33(4): 933-972.

Kirkebøen, Lars, Edwin Leuven, and Magne Mogstad, 2016. "Field of Study, Earnings, and Self-Selection," *The Quarterly Journal of Economics* 131(3): 1057-1111.

Leighton, Margaret and Jamin D. Speer. 2020. "Labor Market Returns to College Major Specificity." *European Economic Review* 128: 103489.

Li, Xiaoxiao, Sebastian Linde, and Hajime Shimao, 2021. "Major Complexity Index and College Skill Production." Villanova University Working Paper.

Lovenheim, Michael and Jonathan Smith. 2023. "Returns to Different Postsecondary Investments: Institution Type, Academic Programs, and Credentials." *Handbook of the Economics of Education* Vol 6: 187-318.

Moffitt, Robert A. and Peter Gottschalk. 2012. "Trends in the Transitory Variance of Male Earnings Methods and Evidence." *Journal of Human Resources* 47(1): 204-236.

Moffitt, Robert and Sisi Zhang. 2018. "The Dynamics of Income: Celebrating 50 Years of the PSID." *AEA Papers and Proceedings* 108: 277-280.

Martin, Shawn M. 2021. "Job Search and Earnings Growth: General and Specific Majors." Working Paper.

Patnaik, Arpita, Joanna Venator, Matthew Wiswall, and Basit Zafar. 2022. "The Role of Heterogeneous Risk Preferences, Discount Rates, and Earnings Expectations in College Major Choice." *Journal of Econometrics* 231(1): 98-122.

Schanzenbach, Diane Whitmore, Ryan Nunn, and Greg Nantz, 2017. "Putting your Major to Work: Career Paths after College." *Hamilton Project Report.*

Stange, Kevin. 2015. "Differential Pricing in Undergraduate Education: Effects on Degree Production by Field." *Journal of Policy Analysis and Management* 34 (1): 107-135.

Stephens, Melvin Jr. 2003. "'3rd of tha Month': Do Social Security Recipients Smooth Consumption between Checks?" *American Economic Review* 93(1): 406-422.

Stevens, A., M. Kurleander, and M. Groz, 2019. Career Technical Education and Labor Market Outcomes: Evidence from California Community Colleges. *Journal of Human Resources* 54(4): 986-1036

Turner, Sarah E., and William G. Bowen. 1999. "Choice of Major: The Changing (Unchanging) Gender Gap." *Industrial and Labor Relations Review* 52(2): 289-313.

Webber, Douglas A. 2014. "The lifetime earnings premia of different majors: Correcting for selection based on cognitive, noncognitive, and unobserved factors." *Labour Economics*, *28*: 14-23

Webber, Douglas A. 2016. "Are college costs worth it? How ability, major, and debt affect the returns to schooling." *Economics of Education Review* 53: 296-310.

Wiswall, Matthew and Basit Zafar. 2015. "Determinants of College Major Choice: Identification using an Information Experiment." *Review of Economic Studies* 82(2): 791-824.

Wiswall, Matthew, and Basit Zafar. 2021. "Human Capital Investments and Expectations about Career and Family." *Journal of Political Economy* 129(5): 1361-1424.

Zeldes, Stephen P. 1989. "Consumption and Liquidity Constraints: An Empirical Investigation." *Journal of Political Economy* 97(2): 305-346.

Table 1: Summary Statistics of Analysis Variables

	4-year Students		2-year Students	
Variable	Mean	SD	Mean	SD
Math Exam Score	0.559	0.696	0.055	0.87
Reading Exam Score	0.515	0.591	0.091	0.826
Top Ten Percent Math	0.260	0.439	0.154	0.361
70th-90th Percentile Math	0.294	0.456	0.183	0.387
Top Ten Percent Reading	0.276	0.447	0.178	0.382
70th-90th Percentile Reading	0.294	0.456	0.191	0.393
Male	0.442	0.497	0.472	0.499
White	0.627	0.484	0.521	0.5
Hispanic	0.219	0.413	0.328	0.469
Black	0.100	0.299	0.126	0.332
Asian	0.053	0.223	0.022	0.148
At Risk	0.175	0.38	0.380	0.485
Economically Disadvantaged	0.164	0.37	0.277	0.447
Earnings 6-10 Years Post-HS	6,788	6,149	5,592	5,258
Earnings 11-15 Years Post-HS	12,338	12,665	8,726	8,386
Earnings 16-20 Years Post-HS	16,793	16,555	11,628	11,636
Liberal Arts	0.215		0.329	
Agriculture	0.034		0.005	
Communications	0.049		0.006	
IT	0.015		0.032	
Vocational	0.080		0.131	
Engineering + Architecture	0.054		0.007	
Biology + Health	0.095		0.137	
Physical Sciences + Math	0.019		0.005	
Social Sciences	0.114		0.033	
Business + Economics	0.198		0.101	
Education			0.036	
Undeclared	0.131		0.184	
Double Major	0.007		0.006	
Max Observations	509,286		554,335	

Authors' tabulations from linked K-12, higher education, and quarterly earnings data in Texas. All earnings are in real 2016 dollars and are at the quarterly level. Math and reading exam scores have been standardized with a mean of 0 and a standard deviation of 1 among the entire student population.

Table 2: The Effect of College Major Choice on Earnings Variability - Residualized Coefficient of Variation, 4-year Students

	Dependent Variable: Residualized Coefficient of Variation Relative to:					
	Linear Prediction		4Q Moving Average	8Q Moving Average	Linear Prediction	
Field of Study	(1)	(2)	(3)	(4)	(5)	(6)
Agriculture	-0.003	0.016	0.012	0.008	0.011	0.004
	(0.021)	(0.012)	(0.009)	(0.010)	(0.013)	(0.006)
Communications	0.015	-0.002	0.000	-0.002	-0.007	0.002
	(0.018)	(0.009)	(0.007)	(0.008)	(0.010)	(0.006)
IT	-0.047	-0.088	-0.054	-0.078	-0.108	-0.064
	(0.017)	(0.016)	(0.009)	(0.012)	(0.021)	(0.013)
Vocational	-0.030	-0.034	-0.026	-0.036	-0.033	-0.023
	(0.018)	(0.009)	(0.006)	(0.007)	(0.010)	(0.006)
Engineering + Architecture	-0.019	-0.047	-0.019	-0.039	-0.062	-0.046
	(0.019)	(0.017)	(0.011)	(0.013)	(0.019)	(0.011)
Biology + Health	0.044	0.047	0.016	0.023	0.061	0.044
	(0.020)	(0.013)	(0.007)	(0.009)	(0.016)	(0.009)
Physical Sciences + Math	0.017	0.007	0.003	0.003	0.012	0.010
	(0.024)	(0.016)	(0.010)	(0.011)	(0.019)	(0.012)
Social Sciences	0.047	0.045	0.027	0.031	0.054	0.031
	(0.017)	(0.009)	(0.006)	(0.007)	(0.010)	(0.006)
Business + Economics	-0.038	-0.050	-0.021	-0.042	-0.062	-0.041
	(0.017)	(0.008)	(0.005)	(0.006)	(0.009)	(0.005)
Undeclared	0.313	0.300	0.168	0.212	0.417	0.254
	(0.022)	(0.014)	(0.007)	(0.009)	(0.019)	(0.011)
Constant	0.717	0.727	0.445	0.577	0.751	0.420
	(0.014)	(0.019)	(0.015)	(0.017)	(0.021)	(0.014)
Frequency	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Annual
Controls		X	X	X	X	X
High School & College FE		X	X	X	X	X
Exclude end of panel					X	
Observations	480,024	479,115	478,782	478,437	450,530	458,133
Dep. Var. Mean	0.756	0.756	0.464	0.587	0.797	0.438

Notes: Authors' estimation as described in the text using linked administrative K-12, higher education, and quarterly earnings data from Texas. Each column is a separate regression. The dependent variable is the residualized coefficient of variation (CV) of earnings for each individual. These CVs are constructed by residualizing earnings relative to predicted earnings ($\bar{Y}_{it}$) and then dividing by the mean of predicted earnings. The number of observations shows the number of unique individuals in the sample. In columns (1)-(2), we use an individual linear earning trend to predict earnings, in columns (3)-(4) we use a 4-quarter moving average, and in columns (4)-(5) we use an 8-quarter moving average. All estimates include cohort fixed effects. "Controls" include standardized 11^{th} grade math and reading exam scores, whether a student is in the top 10 percent of each high school specific test score distribution, whether a student is in the top 10-30 percent of each high school specific test score distribution, gender, race/ethnicity (Black, White, Hispanic, Asian), whether the student was enrolled in a gifted and talented program, an at-risk indicator, and an economic disadvantage indicator. All estimated returns to majors are relative to liberal arts (the excluded category). "Undeclared" status is included in the estimations but not shown. Standard errors clustered at the institution-major level are in parentheses.

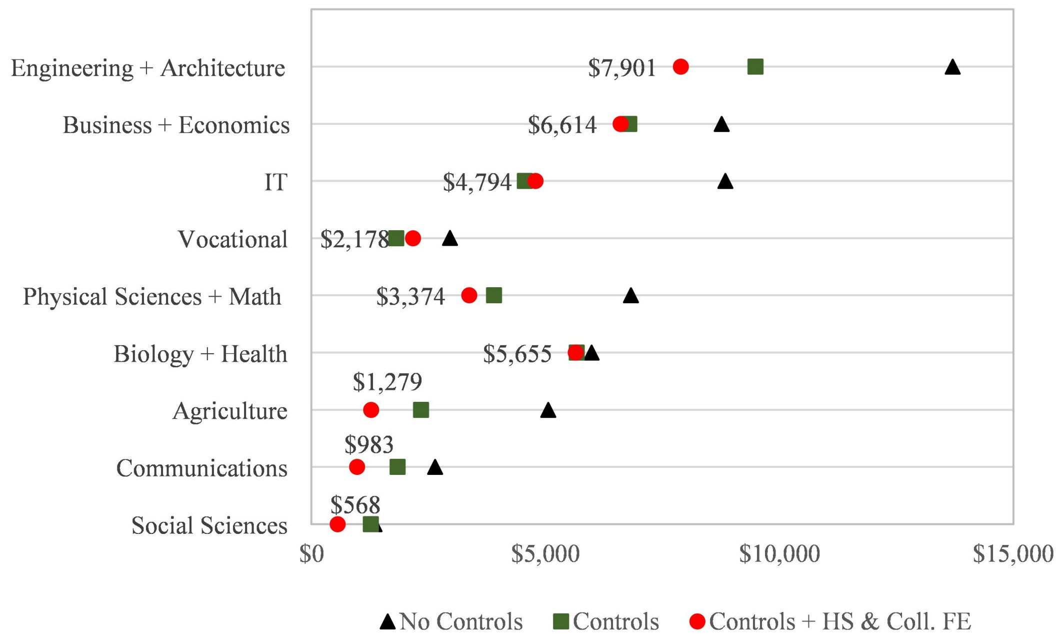
Table 3: The Effect of College Major Choice on Earnings Variability - Residualized Coefficient of Variation, 2-year Students

Dependent Variable: Residualized Coefficient of Variation Relative to:						
			4Q Moving	8Q Moving		
	Linear Prediction		Average	Average	Linear Prediction	
Field of Study	(1)	(2)	(3)	(4)	(5)	(6)
Agriculture	-0.041	-0.010	-0.004	-0.000	0.003	0.003
	(0.022)	(0.016)	(0.011)	(0.016)	(0.019)	(0.013)
Communications	-0.012	-0.012	-0.006	-0.009	-0.015	-0.007
	(0.016)	(0.013)	(0.010)	(0.013)	(0.014)	(0.011)
IT	-0.067	-0.046	-0.029	-0.040	-0.046	-0.033
	(0.012)	(0.008)	(0.006)	(0.007)	(0.009)	(0.006)
Vocational	-0.095	-0.068	-0.044	-0.056	-0.070	-0.040
	(0.013)	(0.007)	(0.004)	(0.006)	(0.008)	(0.005)
Engineering + Architecture	-0.002	0.019	0.025	0.032	0.034	0.019
	(0.015)	(0.013)	(0.010)	(0.012)	(0.017)	(0.013)
Biology + Health	-0.052	-0.057	-0.041	-0.050	-0.047	-0.027
	(0.009)	(0.006)	(0.004)	(0.005)	(0.007)	(0.004)
Physical Sciences + Math	0.040	0.046	0.014	0.024	0.057	0.017
	(0.016)	(0.014)	(0.011)	(0.013)	(0.016)	(0.009)
Social Sciences	0.013	0.005	0.004	0.008	0.017	0.005
	(0.011)	(0.007)	(0.005)	(0.006)	(0.008)	(0.005)
Business + Economics	-0.049	-0.042	-0.024	-0.033	-0.044	-0.028
	(0.009)	(0.006)	(0.004)	(0.005)	(0.007)	(0.004)
Education	-0.022	-0.025	-0.025	-0.028	-0.021	-0.016
	(0.013)	(0.008)	(0.006)	(0.007)	(0.010)	(0.006)
Undeclared	-0.004	0.007	-0.010	-0.006	0.030	0.020
	(0.014)	(0.008)	(0.005)	(0.006)	(0.012)	(0.007)
Constant	0.826	0.914	0.607	0.775	0.920	0.574
	(0.007)	(0.020)	(0.016)	(0.020)	(0.021)	(0.015)
Frequency	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Annual
Controls		X	X	X	X	X
High School & College FE		X	X	X	X	X
Exclude end of panel					X	
Observations	500,521	499,385	498,942	498606	469,793	476,728
Dep. Var. Mean	0.798	0.798	0.522	0.657	0.826	0.497

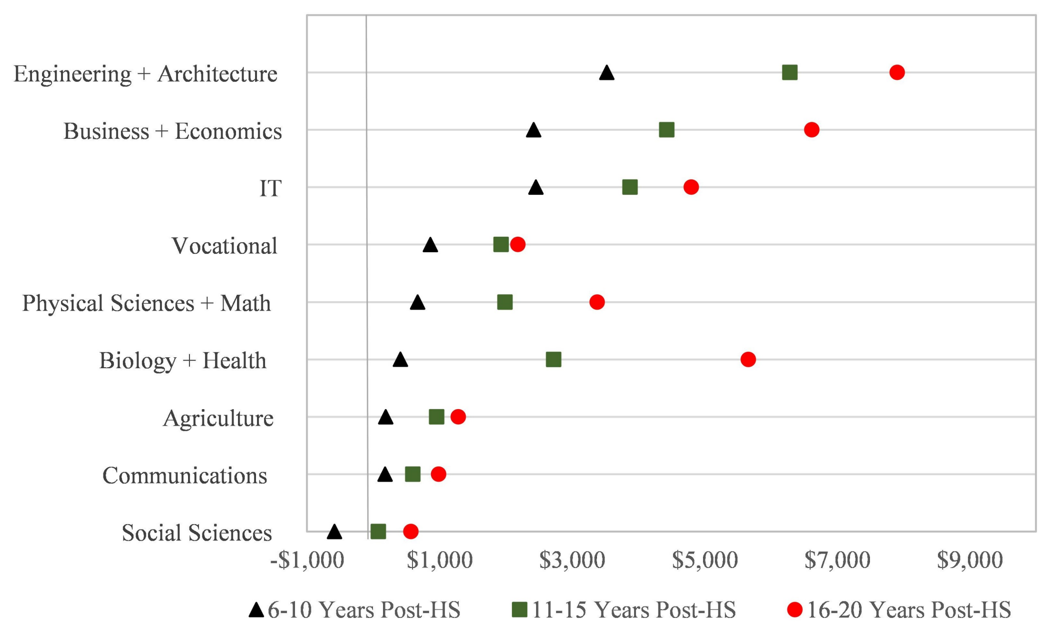
Notes: Authors' estimation as described in the text using linked administrative K-12, higher education, and quarterly earnings data from Texas. Each column is a separate regression. The dependent variable is the residualized coefficient of variation (CV) of earnings for each individual. These CVs are constructed by residualizing earnings relative to predicted earnings ($\bar{Y}_{it}$) and then dividing by the mean of predicted earnings. The number of observations shows the number of unique individuals in the sample. In columns (1)-(2), we use an individual linear earning trend to predict earnings, in columns (3)-(4) we use a 4-quarter moving average, and in columns (4)-(5) we use an 8-quarter moving average. All estimates include cohort fixed effects. "Controls" include standardized 11^{th} grade math and reading exam scores, whether a student is in the top 10 percent of each high school specific test score distribution, whether a student is in the top 10-30 percent of each high school specific test score distribution, gender, race/ethnicity (Black, White, Hispanic, Asian), whether the student was enrolled in a gifted and talented program, an at-risk indicator, and an economic disadvantage indicator. All estimated returns to majors are relative to liberal arts (the excluded category). "Undeclared" status is included in the estimations but not shown. Standard errors clustered at the institution-major level are in parentheses.

Figure 1: Mean Returns and Earnings Growth Effects of College Major - 4-year Students

(a) Mean Returns 16-20 Years Post-HS



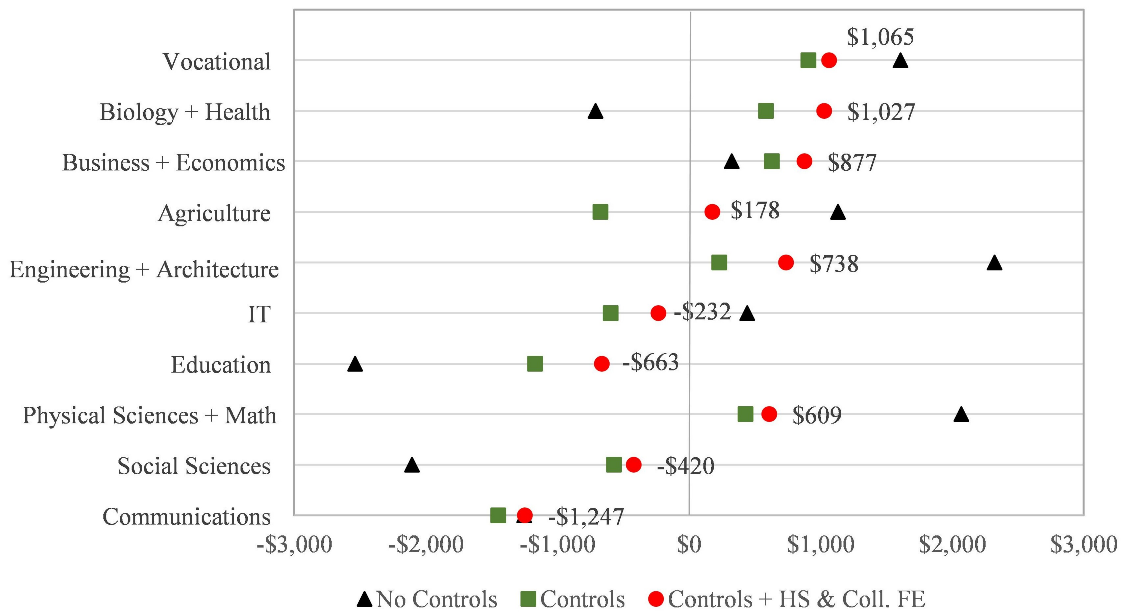
(b) Return to College Major by Potential Experience



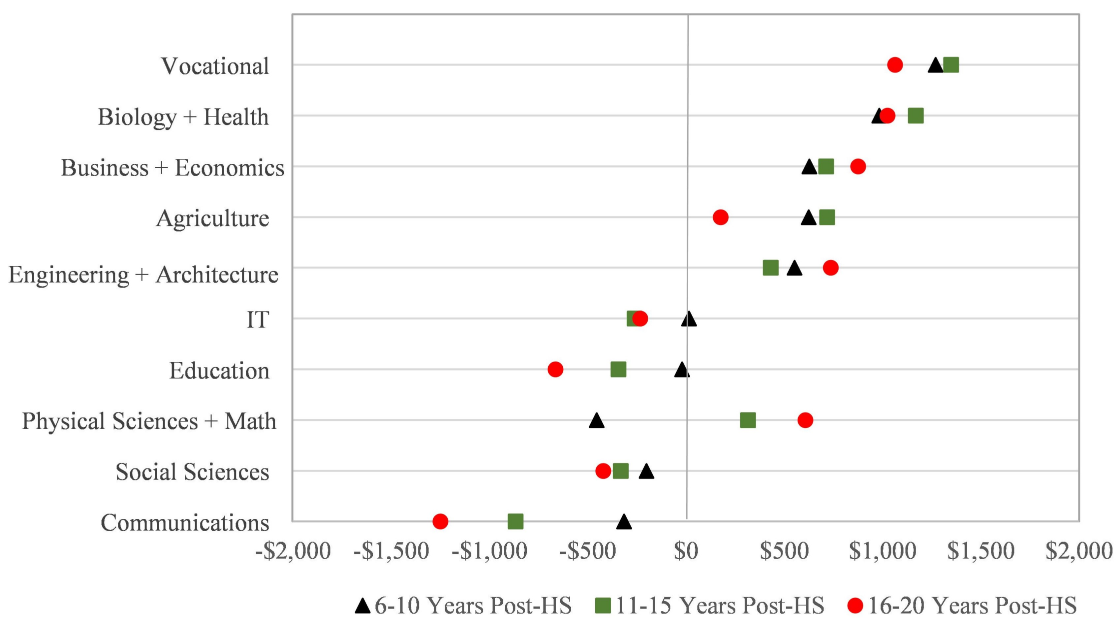
Notes: All estimates are relative to liberal arts majors. "Controls" include measures of high school test scores, and student demographic characteristics. All estimates in panel (b) include controls, HS-by-cohort, and post-secondary institution-by-cohort fixed effects. Outcomes are in dollars of quarterly earnings ($2016).

Figure 2: Mean Returns and Earnings Growth Effects of College Major - 2-year Students

(a) Mean Returns 16-20 Years Post-HS

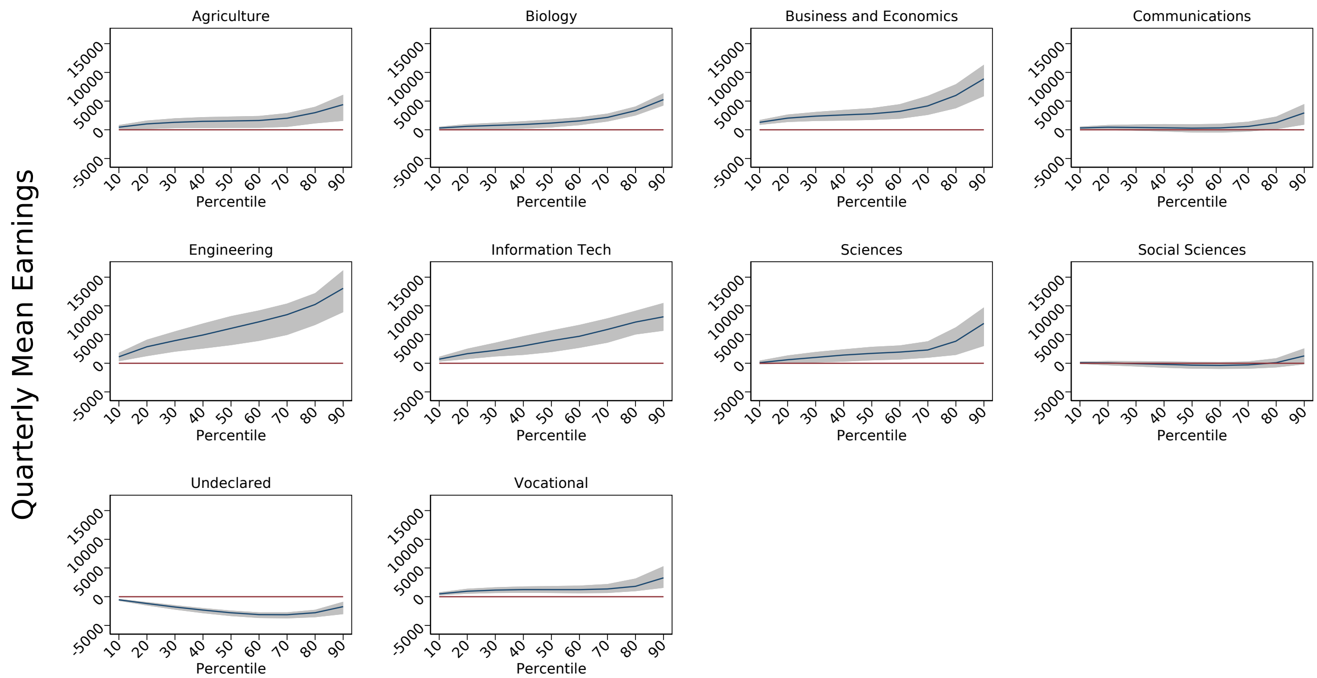


(b) Return to College Major by Potential Experience



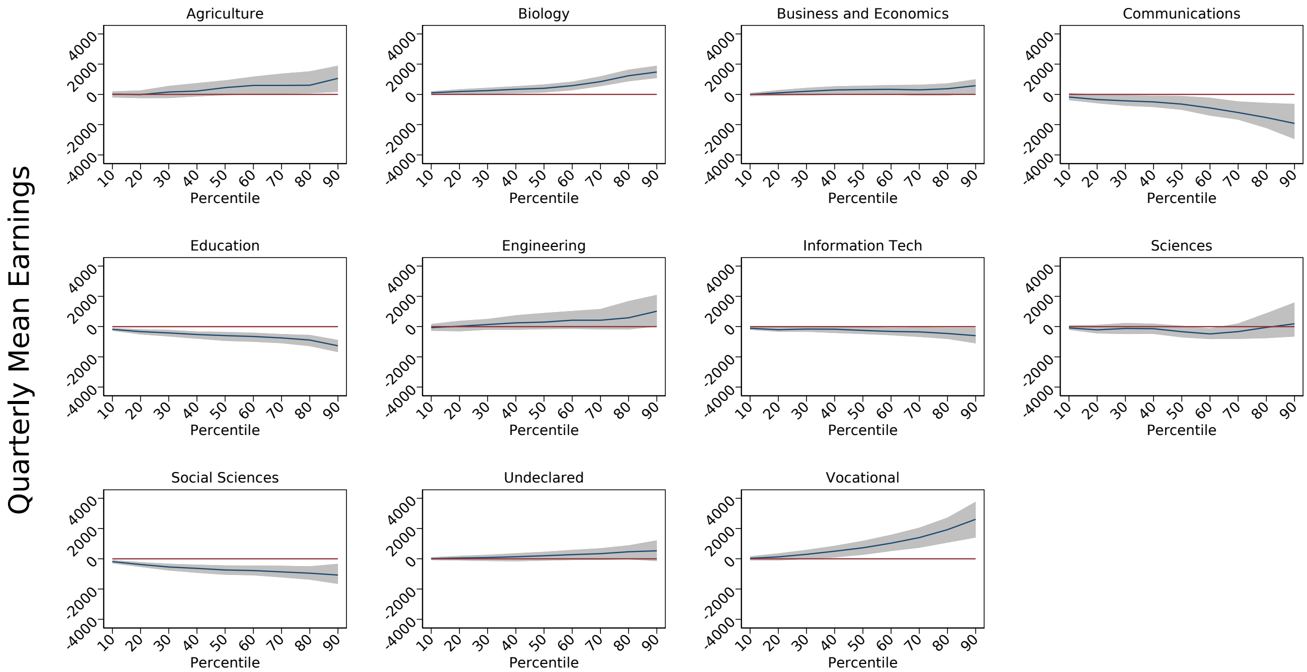
Notes: All estimates are relative to liberal arts majors. "Controls" include measures of high school test scores, and student demographic characteristics. All estimates in panel (b) include controls, HS-by-cohort, and post-secondary institution-by-cohort fixed effects. Outcomes are in dollars of quarterly earnings ($2016).

Figure 3: Quantile Treatment Effects of Major on Average Quarterly Earnings - 4-year Students



Notes: Figure shows quantile treatment effects for each major relative to liberal arts. All estimates include controls for high school test scores, student demographics, HS-by-cohort fixed effects, and college-by-cohort fixed effects. Outcomes are in dollars of quarterly earnings ($2016). The solid curve shows quantile treatment effects for each decile from the 10^{th} to the 90^{th} percentile. The shaded region shows the 95% confidence interval, calculated using a black bootstrap at the postsecondary institution level.

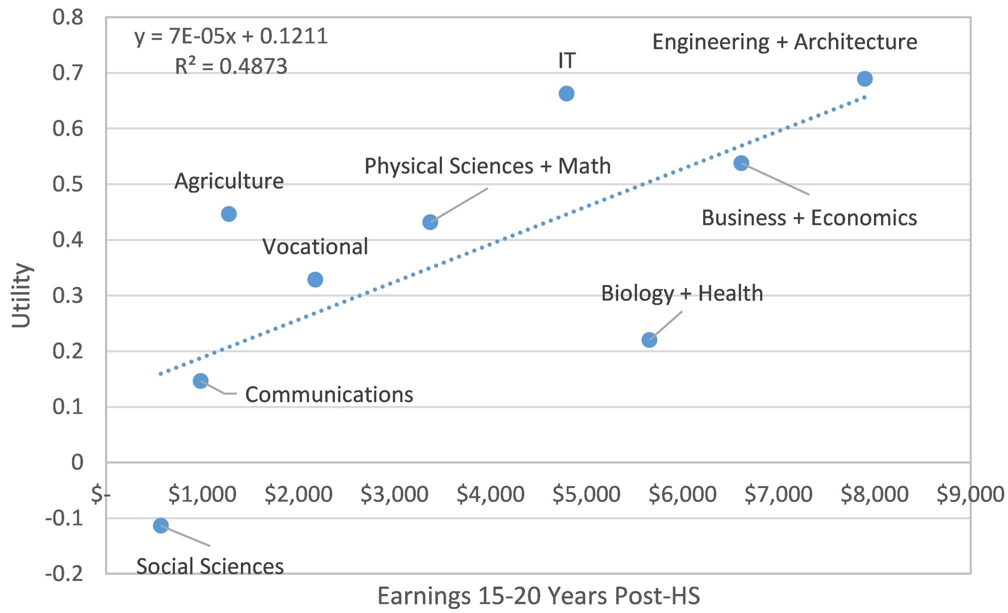
Figure 4: Quantile Treatment Effects of Major on Average Quarterly Earnings - 2-year Students



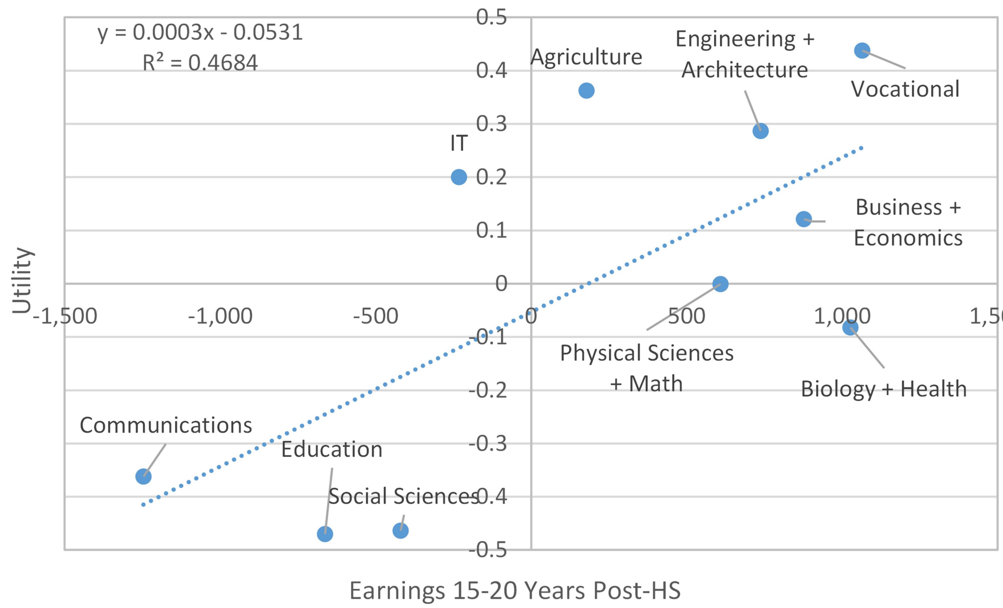
Notes: Figure shows quantile treatment effects for each major relative to liberal arts. All estimates include controls for high school test scores, student demographics, HS-by-cohort fixed effects, and college-by-cohort fixed effects. Outcomes are in dollars of quarterly earnings ($2016). The solid curve shows quantile treatment effects for each decile from the 10^{th} to the 90^{th} percentile. The shaded region shows the 95% confidence interval, calculated using a black bootstrap at the postsecondary institution level.

Figure 5: The Relationship Between Earnings 16-20 Years Post-HS and Utility

(a) 4-year Students



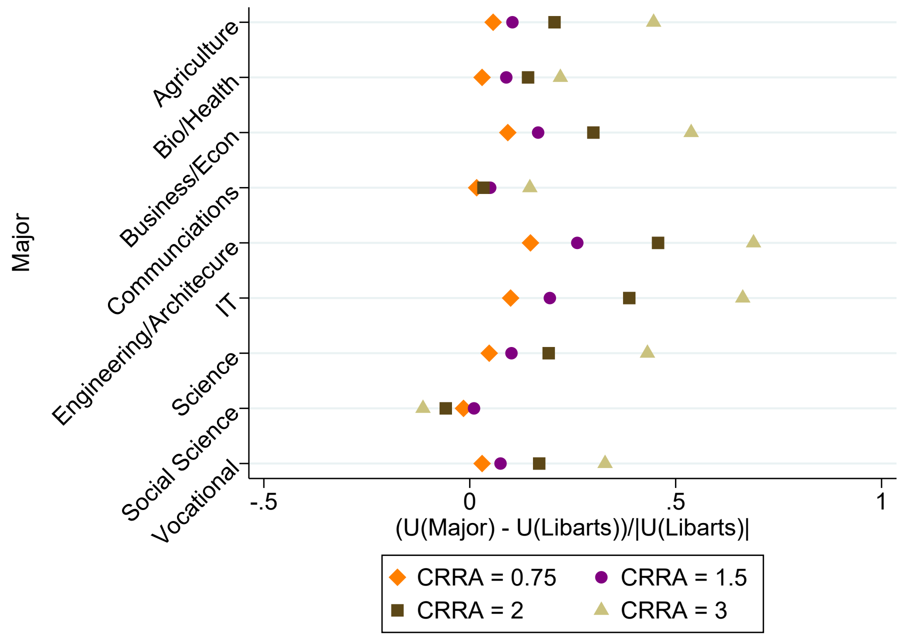
(b) 2-year Students



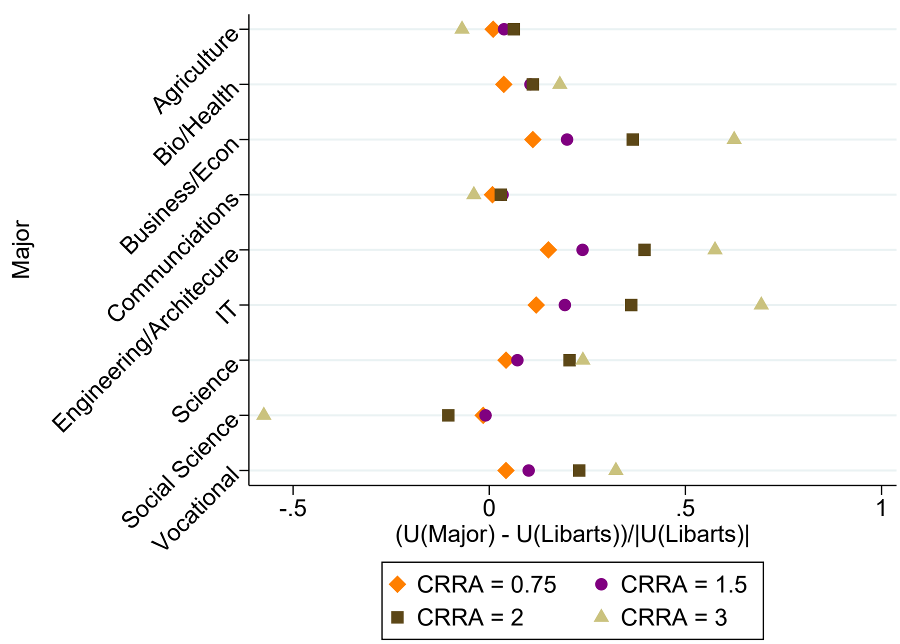
Notes: Earnings estimates include all controls and are for the period 16-20 years after HS graduation. The utility models use a quarterly discount rate of 0.99 and a coefficient of relative risk aversion of 3. Utility estimates using the "Uncertainty, no savings" model with earnings quantiles are shown in the figure. All earnings and utility estimates are relative to liberal arts.

Figure 6: Utility Estimates by Risk Aversion Parameter and the Use of Earnings Quantiles – 4 Year

(a) With Quantiles



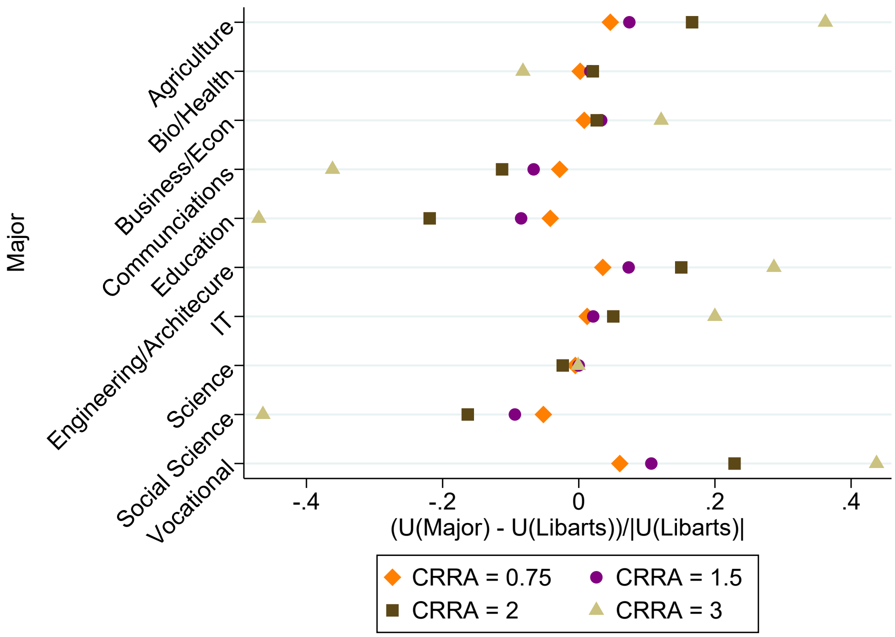
(b) Without Quantiles



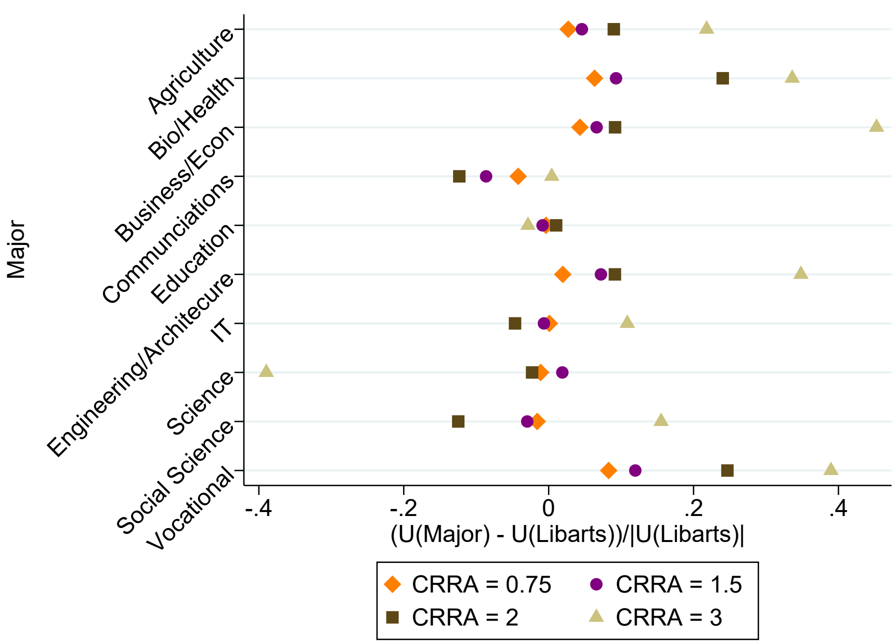
Notes: Utility estimates using the "Uncertainty, no savings" model are shown in the figure and are relative to liberal arts. Panel (a) shows estimates that use quantiles to calculate the initial earnings estimates, while in Panel (b) we use the major-specific intercept shown in Appendix Table A-4.

Figure 7: Utility Estimates by Risk Aversion Parameter and the Use of Earnings Quantiles – 2 Year

(a) With Quantiles



(b) Without Quantiles



Notes: Utility estimates using the "Uncertainty, no savings" model are shown in the figure and are relative to liberal arts. Panel (a) shows estimates that use quantiles to calculate the initial earnings estimates, while in Panel (b) we use the major-specific intercept shown in Appendix Table A-4.

Online Appendix: Not for Publication

Table A-1: Aggregate Major Groups

Aggregate Major Group	Specific Major	CIP Code
Agriculture + Natural Resources	Agriculture, Agriculture Operations, and Related Sciences	01, 02
	Natural Resources and Conservation	03
Communications	Communication, Journalism, and Related Programs	09
Information Technology	Communicatons Technologies/Technicians and Support Services	10
	Computer and Information Sciences and Support Services	11
Vocational	Personal and Culinary Services	12
	Engineering Technologies/Technicians	15
	Vocational Home Economics	20
	Parks, Recreation, Leisure, and Fitness Studies	31
	Basic Skills	32
	Leisure and Recreational Activities	36
	Science Technologies/Technicians	41
	Security and Protective Services	43
	Construction Trades	46
	Mechanic and Repair Technologies/Technicians	47
	Precision Production	48
	Transportation and Materials Moving	49
	Reserve Officer Training Corps	28
	Military Technologies	29
	Citizenship Activities	33
	Health-Related Knowledge and Skills	34
	Interpersonal and Social Skills	35
	Personal Awareness and Self-Improvement	37
Engineering + Architecture	Architecture and Related Services	04
	Engineering	14
Liberal Arts	Area, Ethnic, Cultural, and Gender Studies	05
	Foreign Languaes, Literatures, and Linguistics	16
	English Language and Literature/Letters	23
	Liberal Arts and Sciences, General Studies and Humanities	24
	Library Science	25
	Multi/Interdisciplinary Studies	30
	Philosophy and Religious Studies	38
	Theology and Religious Vocations	39
	Visual and Performing Arts	50
	History	4508, 54
Biology + Health	Biological and Biomedical Sciences	26
	Health Professions and Related Clinical Sciences	51
	Residency Programs	60
Physical Sciences + Math	Physical Sciences	40
	Mathematics and Statistics	27
Social Sciences	Family and Consumer Sciences/Human Sciences	19
	Legal Professions and Studies	22
	Psychology	42
	Public Administration and Social Service Professions	44
	Social Sciences, General	4501
	Anthropology	4502
	Archeology	4503
	Criminology	4504

Continued on next page

Aggregate Major Group	Specific Major	CIP Code
	Demography and Population Studies	4505
	Geography and Cartography	4507
	International Relations and Affairs	4509
	Political Science and Government	4510
	Sociology	4511
	Urban Studies/Affairs	4512
	Sociology and Anthropology	4513
	Rural Sociology	4514
	Social Sciences, Other	4599
Business + Economics	Business, Management, Marketing, and Related Support Services	52, 08
	Economics	4506
Education (2-year only)	Education	13
Undeclared		99

Source: Texas Higher Education Coordinating Board data as described in the text.

Table A-2: Selection Into the Earnings Sample

Field of Study	Four-year Quarters Non-Zero Earnings (1)	Four-year Quarters Zero Earnings (2)	Four-year I(Leave Earnings Sample) (3)	Two-year Quarters Non-Zero Earnings (4)	Two-year Quarters Zero Earnings (5)	Two-year I(Leave Earnings Sample) (6)
Agriculture	-2.42	0.81	0.08	-1.58	-1.45	-0.04
	(0.616)	(0.308)	(0.014)	(0.606)	(0.377)	(0.023)
Communications	-2.34	0.66	0.05	-0.93	-2.38	-0.06
	(0.530)	(0.241)	(0.013)	(0.562)	(0.343)	(0.022)
IT	-0.96	-0.39	-0.00	-0.18	-2.84	-0.09
	(0.609)	(0.312)	(0.017)	(0.529)	(0.301)	(0.020)
Vocational	-0.99	0.02	0.04	0.74	-2.93	-0.10
	(0.498)	(0.232)	(0.012)	(0.510)	(0.284)	(0.020)
Engineering + Architecture	-1.46	-0.06	0.03	-1.59	-1.85	-0.05
	(0.581)	(0.292)	(0.017)	(0.581)	(0.323)	(0.021)
Biology + Health	-2.77	1.63	0.10	0.85	-3.22	-0.09
	(0.508)	(0.274)	(0.015)	(0.506)	(0.280)	(0.020)
Physical Sciences + Math	-2.63	0.87	0.05	-1.78	-2.06	-0.04
	(0.561)	(0.293)	(0.015)	(0.538)	(0.334)	(0.020)
Social Sciences	-3.29	1.29	0.11	-1.19	-2.06	-0.05
	(0.508)	(0.231)	(0.013)	(0.520)	(0.290)	(0.020)
Business + Economics	-0.16	-0.46	-0.00	0.24	-2.94	-0.10
	(0.485)	(0.219)	(0.012)	(0.508)	(0.283)	(0.020)
Education				-0.28	-2.37	-0.07
				(0.510)	(0.296)	(0.020)
Constant	34.49	6.19	0.58	30.26	11.32	0.77
	(0.758)	(0.445)	(0.023)	(0.718)	(0.450)	(0.025)
Controls	X	X	X	X	X	X
High School & College FE	X	X	X	X	X	X
Observations	386,471	386,471	386,471	342,036	342,036	342,036

Notes: Authors' estimation as described in the text using linked administrative K-12, higher education, and quarterly earnings data from Texas. Quarters of zero and non-zero earnings include counts of quarters in which an individual is not enrolled in a postsecondary institution and is between non-zero earnings spells in Texas. Those who exit the earnings sample are those for whom we observe positive earnings after enrollment followed by no earnings. Each column is a separate regression. The number of observations shows the number of unique individuals in the sample. "Controls" are the same as those listed in Table 2. All estimated returns to majors are relative to liberal arts (the excluded category). Standard errors clustered at the institution-major level are in parentheses.

Table A-3: Means of Analysis Variables by Major

4-year Students

Variable	Liberal Arts	Agri-culture	Comm-unications	IT	Voc-ational	Eng. & Arch.	Bio & Health	Science & Math	Social Science	Bus. & Econ.	Educ-ation	Undec-lared
Math Exam Score	0.475	0.607	0.531	0.865	0.394	0.969	0.655	0.969	0.513	0.681		0.337
Reading Exam Score	0.521	0.546	0.611	0.617	0.347	0.677	0.581	0.673	0.570	0.538		0.352
Top Ten Percent Math	0.212	0.248	0.231	0.445	0.182	0.517	0.309	0.508	0.227	0.301		0.185
70th-90th Percentile Math	0.286	0.327	0.300	0.316	0.273	0.299	0.308	0.312	0.298	0.326		0.245
Top Ten Percent Reading	0.281	0.276	0.316	0.346	0.192	0.379	0.314	0.364	0.299	0.276		0.207
70th-90th Percentile Reading	0.293	0.309	0.320	0.314	0.258	0.317	0.305	0.324	0.308	0.302		0.256
Male	0.306	0.609	0.364	0.850	0.618	0.754	0.285	0.549	0.292	0.530		0.464
White	0.668	0.905	0.663	0.632	0.584	0.655	0.539	0.673	0.629	0.648		0.513
Hispanic	0.225	0.064	0.184	0.164	0.240	0.197	0.242	0.207	0.212	0.177		0.317
Black	0.079	0.025	0.111	0.085	0.154	0.054	0.117	0.052	0.115	0.092		0.125
Asian	0.026	0.005	0.040	0.117	0.020	0.092	0.100	0.065	0.043	0.082		0.042
At Risk	0.179	0.128	0.143	0.136	0.225	0.103	0.150	0.105	0.164	0.142		0.272
Economically Disadvantaged	0.162	0.055	0.107	0.152	0.202	0.138	0.193	0.156	0.152	0.133		0.235
Earnings 6-10 Years Post-HS	6,170	7,395	6,635	8,874	6,869	10,651	6,778	7,534	5,834	8,844		3,460
Earnings 11-15 Years Post-HS	10,267	13,393	11,682	16,092	12,434	19,700	13,258	14,246	10,816	15,773		7,684
Earnings 16-20 Years Post-HS	13,018	18,031	15,654	21,988	15,895	26,691	18,931	20,056	14,330	21,694		12,331

2-year Students

Variable	Liberal Arts	Agri-culture	Comm-unications	IT	Voc-ational	Eng. & Arch.	Bio & Health	Science & Math	Social Science	Bus. & Econ.	Educ-ation	Undec-lared
Math Exam Score	0.090	0.017	0.012	0.097	-0.124	0.356	0.005	0.540	-0.098	0.071	-0.108	0.176
Reading Exam Score	0.153	0.019	0.260	0.031	-0.172	0.156	0.089	0.357	0.079	0.050	-0.014	0.207
Top Ten Percent Math	0.154	0.149	0.137	0.176	0.164	0.218	0.125	0.275	0.129	0.142	0.116	0.177
70th-90th Percentile Math	0.193	0.176	0.181	0.199	0.141	0.254	0.172	0.296	0.153	0.189	0.144	0.207
Top Ten Percent Reading	0.184	0.173	0.202	0.173	0.173	0.179	0.158	0.219	0.176	0.154	0.144	0.203
70th-90th Percentile Reading	0.205	0.171	0.232	0.181	0.132	0.214	0.188	0.266	0.188	0.181	0.172	0.217
Male	0.458	0.811	0.519	0.760	0.766	0.873	0.242	0.570	0.236	0.466	0.306	0.452
White	0.552	0.877	0.504	0.485	0.480	0.451	0.500	0.528	0.462	0.477	0.462	0.554
Hispanic	0.287	0.092	0.363	0.331	0.395	0.441	0.363	0.371	0.380	0.354	0.423	0.287
Black	0.132	0.029	0.121	0.155	0.111	0.083	0.114	0.070	0.145	0.146	0.106	0.125
Asian	0.026	0.001	0.008	0.026	0.011	0.024	0.021	0.028	0.010	0.020	0.006	0.031
At Risk	0.358	0.366	0.373	0.405	0.478	0.351	0.387	0.267	0.415	0.379	0.418	0.330
Economically Disadvantaged	0.243	0.120	0.262	0.305	0.345	0.334	0.313	0.269	0.328	0.293	0.368	0.224
Earnings 6-10 Years Post-HS	5270	6,613	4,721	5,549	6,729	6,244	5,669	5,077	4,380	5,727	4,592	5,625
Earnings 11-15 Years Post-HS	8527	9,989	7,421	8,651	10,082	10,042	8,477	9,637	6,815	8,801	6,845	8,960
Earnings 16-20 Years Post-HS	11435	12,462	10,157	11,722	12,776	13,706	10,680	13,451	9,229	11,672	8,886	12,587

Authors' tabulations from linked K-12, higher education, and quarterly earnings data in Texas. All earnings are in real 2016 dollars and are at the quarterly level. Math and reading exam scores have been standardized with a mean of 0 and a standard deviation of 1 among the entire student population.

Table A-4: Effect of Major Choice on Components of Wage Decomposition

	4-year Students				2-year Students			
	α		β		α		β	
Field of Study	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agriculture	1,106.669	124.126	29.753	11.961	1,232.118	473.634	6.365	3.193
	(398.789)	(291.232)	(6.152)	(3.753)	(342.809)	(273.266)	(3.540)	(3.430)
Communications	515.929	317.128	11.814	3.001	-569.464	-310.973	-4.009	-5.985
	(363.924)	(199.598)	(4.881)	(3.549)	(187.465)	(135.727)	(2.815)	(2.954)
IT	2,223.214	2,154.616	56.333	26.781	347.240	42.687	2.368	-3.192
	(580.783)	(430.719)	(7.900)	(3.521)	(195.205)	(108.472)	(1.689)	(1.134)
Vocational	771.558	952.730	19.212	12.256	1,720.801	1,399.865	1.610	-1.243
	(348.799)	(143.593)	(5.036)	(2.437)	(300.734)	(117.222)	(1.847)	(0.926)
Engineering + Architecture	4,231.185	3,506.859	69.355	35.451	1,129.701	747.775	5.302	-5.944
	(817.894)	(479.796)	(8.475)	(4.370)	(326.580)	(198.092)	(2.706)	(2.886)
Biology + Health	138.867	120.482	44.053	40.746	451.007	1,054.388	-4.517	1.753
	(319.394)	(409.915)	(8.108)	(4.331)	(169.752)	(66.864)	(1.369)	(0.843)
Physical Sciences + Math	871.231	433.165	42.436	21.979	-194.763	-330.596	17.429	7.475
	(682.102)	(434.095)	(5.593)	(5.884)	(231.826)	(157.930)	(3.596)	(2.948)
Social Sciences	-338.375	-495.106	10.212	6.329	-792.328	-99.185	-9.259	-3.537
	(252.210)	(182.869)	(4.798)	(3.073)	(202.660)	(83.911)	(1.940)	(1.126)
Business + Economics	2,745.058	2,573.439	42.494	28.267	537.175	682.156	0.287	0.915
	(566.060)	(299.210)	(7.181)	(3.547)	(184.147)	(76.934)	(1.333)	(0.808)
Education					-647.122	83.193	-11.408	-5.647
					(190.466)	(98.776)	(1.933)	(1.295)
Undeclared	-2,696.426	-2,200.990	16.426	14.000	362.775	256.395	8.233	6.065
	(257.710)	(211.633)	(3.861)	(2.719)	(204.829)	(85.253)	(2.083)	(0.903)
Constant	6,069.969	5,564.723	53.203	38.663	5,293.600	3,701.744	42.203	29.767
	(178.915)	(239.911)	(2.080)	(4.567)	(136.840)	(154.330)	(1.012)	(2.324)
Controls		X		X		X		X
High School & College FE		X		X		X		X
Observations	491,408	490,488	491,408	490,488	509,151	508,011	509,151	508,011
Dep. Var. Mean	6613	6613	77.48	77.48	5582	5582	41.88	41.88

Notes: Authors' estimation as described in the text using linked administrative K-12, higher education, and quarterly earnings data from Texas. The values in the table are coefficients from components of equation (1) on major choice. β is the slope of earnings with respect to quarters after high school. α is the y-intercept that is calculated using earnings 5 years after high school extrapolated to time 0 using the slope (e.g. estimated starting wage). Each column is a separate regression. The number of observations shows the number of unique individuals in the sample. All estimates include high school cohort fixed effects. "Controls" are the same as those listed in Table 2. All estimated returns to majors are relative to liberal arts (the excluded category). Standard errors clustered at the institution-major level are in parentheses.

Table A-5: Returns to College Major Relative to Liberal Arts, by Years Relative to HS - 4-year Students

	6-10 Years Post-HS			11-15 Years Post-HS			16-20 Years Post-HS		
Agriculture	1,187	892	185	3,149	1,794	954	5,063	2,349	1,279
	(425)	(326)	(281)	(759)	(613)	(498)	(1,087)	(863)	(870)
Communications	439	330	177	1,422	1,040	596	2,650	1,848	983
	(373)	(248)	(196)	(682)	(444)	(381)	(1,139)	(738)	(591)
IT	2,648	2,351	2,454	5,765	3,614	3,873	8,847	4,562	4,794
	(605)	(521)	(405)	(1,040)	(824)	(582)	(1,466)	(1,095)	(599)
Vocational	686	923	863	2,238	1,851	1,926	2,964	1,817	2,178
	(365)	(253)	(143)	(638)	(411)	(276)	(1,036)	(648)	(402)
Engineering + Architecture	4,453	3,981	3,521	9,455	7,221	6,282	13,708	9,494	7,901
	(840)	(687)	(469)	(1,336)	(1,051)	(672)	(1,954)	(1,498)	(828)
Biology + Health	580	484	413	3,020	2,796	2,718	5,995	5,676	5,655
	(274)	(253)	(361)	(473)	(266)	(386)	(1,248)	(803)	(461)
Physical Sciences + Math	1,256	759	666	3,831	2,212	1,985	6,833	3,909	3,374
	(607)	(525)	(316)	(750)	(594)	(380)	(1,246)	(957)	(595)
Social Sciences	-377	-412	-587	549	506	76	1,355	1,276	568
	(267)	(174)	(190)	(509)	(285)	(347)	(920)	(514)	(560)
Business + Economics	2,654	2,495	2,418	5,546	4,554	4,425	8,774	6,799	6,614
	(576)	(454)	(293)	(972)	(722)	(479)	(1,596)	(1,157)	(701)
Undeclared	-2,735	-2,401	-2,196	-2,526	-2,403	-1,993	-565	-536	85
	(260)	(232)	(215)	(368)	(289)	(315)	(613)	(408)	(445)
Constant	6,214	5,395	5,605	10,239	8,233	8,658	12,941	9,662	10,345
	(186)	(234)	(209)	(234)	(314)	(383)	(477)	(625)	(684)
Controls		X	X		X	X		X	X
High School & College FE			X			X			X
Observations	490,727	490,727	489,804	445,103	445,103	444,171	268,900	268,900	268,247
Dep. Var. Mean	6,790	6,790	6,790	12,336	12,336	12,336	16,803	16,803	16,803

Notes: Authors' estimation as described in the text using linked administrative K-12, higher education, and quarterly earnings data from Texas. Each column is a separate regression, with average quarterly earnings at the individual level as the dependent variable. The number of observations shows the number of unique individuals in the sample. All estimates include high school cohort fixed effects. "Controls" include standardized 11^{th} grade math and reading exam scores, whether a student is in the top 10 percent of each high school specific test score distribution, whether a student is in the top 10-30 percent of each high school specific test score distribution, gender, race/ethnicity (Black, White, Hispanic, Asian), whether the student was enrolled in a gifted and talented program, an at-risk indicator, and an economic disadvantage indicator. All estimated returns to majors are relative to liberal arts (the excluded category). Standard errors clustered at the institution-major level are in parentheses.

Table A-6: Returns to College Major Relative to Liberal Arts, by Years Relative to HS - 2-year Students

	6-10 Years Post-HS			11-15 Years Post-HS			16-20 Years Post-HS		
Field of Study	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Agriculture	1,319	548	626	1,550	168	720	1,132	-673	178
	(249)	(213)	(174)	(417)	(346)	(235)	(449)	(369)	(289)
Communications	-546	-574	-313	-1,070	-1,151	-866	-1,252	-1,449	-1,247
	(184)	(189)	(125)	(285)	(315)	(234)	(490)	(501)	(446)
IT	329	-52	16	245	-571	-260	442	-596	-232
	(174)	(120)	(85)	(280)	(177)	(138)	(439)	(271)	(231)
Vocational	1,566	1,310	1,271	1,791	1,266	1,350	1,606	907	1,065
	(284)	(222)	(110)	(411)	(312)	(158)	(506)	(362)	(184)
Engineering + Architecture	972	272	554	1,555	46	432	2,322	231	738
	(276)	(219)	(147)	(404)	(303)	(222)	(558)	(385)	(346)
Biology + Health	412	840	985	8	886	1,170	-709	585	1,027
	(156)	(110)	(64)	(235)	(166)	(90)	(321)	(223)	(122)
Physical Sciences + Math	-242	-690	-453	1,131	116	317	2,069	431	609
	(199)	(156)	(127)	(398)	(330)	(223)	(693)	(602)	(426)
Social Sciences	-867	-353	-200	-1,624	-558	-330	-2,105	-571	-420
	(178)	(113)	(69)	(314)	(193)	(106)	(470)	(281)	(142)
Business + Economics	482	552	628	340	495	714	325	630	877
	(171)	(122)	(73)	(257)	(170)	(92)	(364)	(237)	(136)
Education	-688	-257	-18	-1,665	-758	-342	-2,536	-1,170	-663
	(182)	(123)	(89)	(237)	(145)	(116)	(340)	(228)	(160)
Undeclared	357	299	260	496	359	467	1,234	1,069	1,134
	(195)	(159)	(85)	(295)	(226)	(104)	(414)	(315)	(140)
Constant	5,336	4,217	3,956	8,592	6,259	5,949	11,509	8,005	7,599
	(128)	(151)	(140)	(195)	(249)	(231)	(273)	(424)	(383)
Controls		X	X		X	X		X	X
High School & College FE			X			X			X
Observations	508,314	508,314	507,175	466,289	466,289	465,146	277,346	277,346	276,553
Dep. Var. Mean	5,592	5,592	5,592	8,726	8,726	8,726	11,628	11,628	11,628

Notes: Authors' estimation as described in the text using linked administrative K-12, higher education, and quarterly earnings data from Texas. Each column is a separate regression, with average quarterly earnings at the individual level as the dependent variable. The number of observations shows the number of unique individuals in the sample. All estimates include high school cohort fixed effects. "Controls" include standardized 11^{th} grade math and reading exam scores, whether a student is in the top 10 percent of each high school specific test score distribution, whether a student is in the top 10-30 percent of each high school specific test score distribution, gender, race/ethnicity (Black, White, Hispanic, Asian), whether the student was enrolled in a gifted and talented program, an at-risk indicator, and an economic disadvantage indicator. All estimated returns to majors are relative to liberal arts (the excluded category). Standard errors clustered at the institution-major level are in parentheses.

Table A-7: The Effect of College Major Choice on Earnings Variability - Standard Deviation of Residual Earnings, 4-year Students

	Dependent Variable: Standard Deviation of Residual Earnings Relative to:					
	Linear Prediction		4Q Moving Average	8Q Moving Average	Linear Prediction	
Field of Study	(1)	(2)	(3)	(4)	(5)	(6)
Agriculture	1443.78	668.45	430.60	446.49	622.19	394.02
	(314.12)	(164.52)	(106.02)	(122.09)	(124.49)	(73.12)
Communications	820.75	454.27	300.52	301.16	327.35	258.24
	(279.25)	(123.16)	(78.36)	(91.69)	(107.02)	(58.61)
IT	2012.50	1063.19	691.32	709.48	909.56	338.98
	(355.28)	(144.27)	(103.19)	(115.23)	(131.74)	(65.37)
Vocational	883.20	774.43	432.25	497.85	718.05	403.15
	(274.91)	(104.37)	(63.65)	(70.38)	(93.81)	(49.28)
Engineering + Architecture	3501.47	2251.21	1489.19	1648.60	2016.55	943.36
	(466.56)	(203.34)	(140.19)	(158.18)	(172.05)	(75.69)
Biology + Health	1745.55	1693.05	878.70	1130.27	1447.32	1113.33
	(254.03)	(104.11)	(73.97)	(80.78)	(91.01)	(56.64)
Physical Sciences + Math	1701.93	1002.74	590.54	670.94	826.97	505.71
	(284.09)	(120.93)	(74.93)	(85.68)	(104.59)	(70.39)
Social Sciences	522.50	350.94	176.61	181.30	250.70	243.51
	(239.65)	(108.84)	(72.46)	(80.89)	(88.84)	(51.75)
Business + Economics	2219.38	1731.41	1197.29	1292.30	1429.49	734.16
	(325.55)	(134.77)	(98.99)	(112.36)	(110.77)	(60.51)
Undeclared	770.08	804.24	403.03	469.91	447.63	685.05
	(160.40)	(97.87)	(66.00)	(77.11)	(82.73)	(52.09)
Constant	4138.84	3603.68	2053.39	2708.59	3452.59	2146.09
	(119.44)	(145.07)	(93.80)	(106.05)	(123.44)	(88.84)
Frequency	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Annual
Controls		X	X	X	X	X
High School & College FE		X	X	X	X	X
Exclude end of panel					X	
Observations	479,961	479,045	482,236	481,841	464,073	458,045
Dep. Var. Mean	5314	5314	3062	3863	4867	3034

Notes: Authors' estimation as described in the text using linked administrative K-12, higher education, and quarterly earnings data from Texas. Each column is a separate regression. The dependent variable is the residualized standard deviation of earnings of each individual, where residuals are relative to predicted earnings ($\bar{Y}_{it}$) that are constructed differently across columns as indicated. The number of observations shows the number of unique individuals in the sample. In columns (1)-(2), we use an individual linear earning trend to predict earnings, in columns (3)-(4) we use a 4-quarter moving average, and in columns (4)-(5) we use an 8-quarter moving average. All estimates include cohort fixed effects. "Controls" include standardized 11^{th} grade math and reading exam scores, whether a student is in the top 10 percent of each high school specific test score distribution, whether a student is in the top 10-30 percent of each high school specific test score distribution, gender, race/ethnicity (Black, White, Hispanic, Asian), whether the student was enrolled in a gifted and talented program, an at-risk indicator, and an economic disadvantage indicator. All estimated returns to majors are relative to liberal arts (the excluded category). "Undeclared" status is included in the estimations but not shown. Standard errors clustered at the institution-major level are in parentheses.

Table A-8: The Effect of College Major Choice on Earnings Variability - Standard Deviation of Residual Earnings, 2-year Students

	Dependent Variable: Standard Deviation of Residual Earnings Relative to:					
	Linear Prediction		4Q Moving Average	8Q Moving Average	Linear Prediction	
Field of Study	(1)	(2)	(3)	(4)	(5)	(6)
Agriculture	461.01	312.06	250.58	301.06	291.30	185.57
	(105.41)	(65.56)	(42.55)	(52.74)	(61.36)	(40.94)
Communications	-329.67	-255.55	-120.89	-151.99	-196.39	-148.40
	(97.63)	(73.25)	(43.48)	(53.81)	(70.04)	(37.37)
IT	43.87	-162.22	-102.85	-139.64	-144.18	-134.15
	(106.54)	(63.28)	(37.03)	(43.30)	(55.27)	(35.50)
Vocational	479.69	359.03	257.16	298.10	366.75	182.39
	(129.48)	(49.32)	(30.77)	(35.86)	(47.07)	(26.95)
Engineering + Architecture	722.17	377.27	256.26	316.17	331.48	225.14
	(157.87)	(85.36)	(57.15)	(73.26)	(81.30)	(57.09)
Biology + Health	163.26	522.74	343.25	437.51	571.31	347.69
	(81.04)	(33.95)	(19.58)	(23.67)	(32.80)	(21.12)
Physical Sciences + Math	520.08	260.32	63.53	126.99	170.02	163.86
	(150.63)	(89.29)	(50.20)	(66.99)	(81.38)	(72.26)
Social Sciences	-495.90	-141.23	-88.85	-116.58	-120.74	-101.64
	(107.07)	(38.34)	(24.40)	(31.59)	(36.65)	(27.40)
Business + Economics	155.62	224.60	168.35	184.00	204.47	97.39
	(89.71)	(36.92)	(21.81)	(26.67)	(34.42)	(23.70)
Education	-653.56	-212.91	-145.72	-170.74	-183.56	-140.48
	(79.84)	(37.91)	(23.40)	(28.88)	(37.37)	(26.17)
Undeclared	387.80	330.12	146.92	211.21	245.73	248.97
	(90.12)	(40.44)	(21.10)	(26.71)	(37.16)	(29.36)
Constant	3773.59	3019.15	1869.06	2401.07	2808.32	1964.83
	(65.70)	(69.78)	(43.28)	(54.59)	(71.56)	(49.59)
Frequency	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Annual
Controls		X	X	X	X	X
High School & College FE		X	X	X	X	X
Exclude end of panel					X	
Observations	500,196	499,051	500,089	499730	483,718	476,535
Dep. Var. Mean	3913	3913	2395	3019	3631	2442

Notes: Authors' estimation as described in the text using linked administrative K-12, higher education, and quarterly earnings data from Texas. Each column is a separate regression. The dependent variable is the residualized standard deviation of earnings of each individual, where residuals are relative to predicted earnings ($\bar{Y}_{it}$) that are constructed differently across columns as indicated. The number of observations shows the number of unique individuals in the sample. In columns (1)-(2), we use an individual linear earning trend to predict earnings, in columns (3)-(4) we use a 4-quarter moving average, and in columns (4)-(5) we use an 8-quarter moving average. All estimates include cohort fixed effects. "Controls" include standardized 11^{th} grade math and reading exam scores, whether a student is in the top 10 percent of each high school specific test score distribution, whether a student is in the top 10-30 percent of each high school specific test score distribution, gender, race/ethnicity (Black, White, Hispanic, Asian), whether the student was enrolled in a gifted and talented program, an at-risk indicator, and an economic disadvantage indicator. All estimated returns to majors are relative to liberal arts (the excluded category). "Undeclared" status is included in the estimations but not shown. Standard errors clustered at the institution-major level are in parentheses.

Figure A-1: Linear Earnings Growth Over Time, by Field

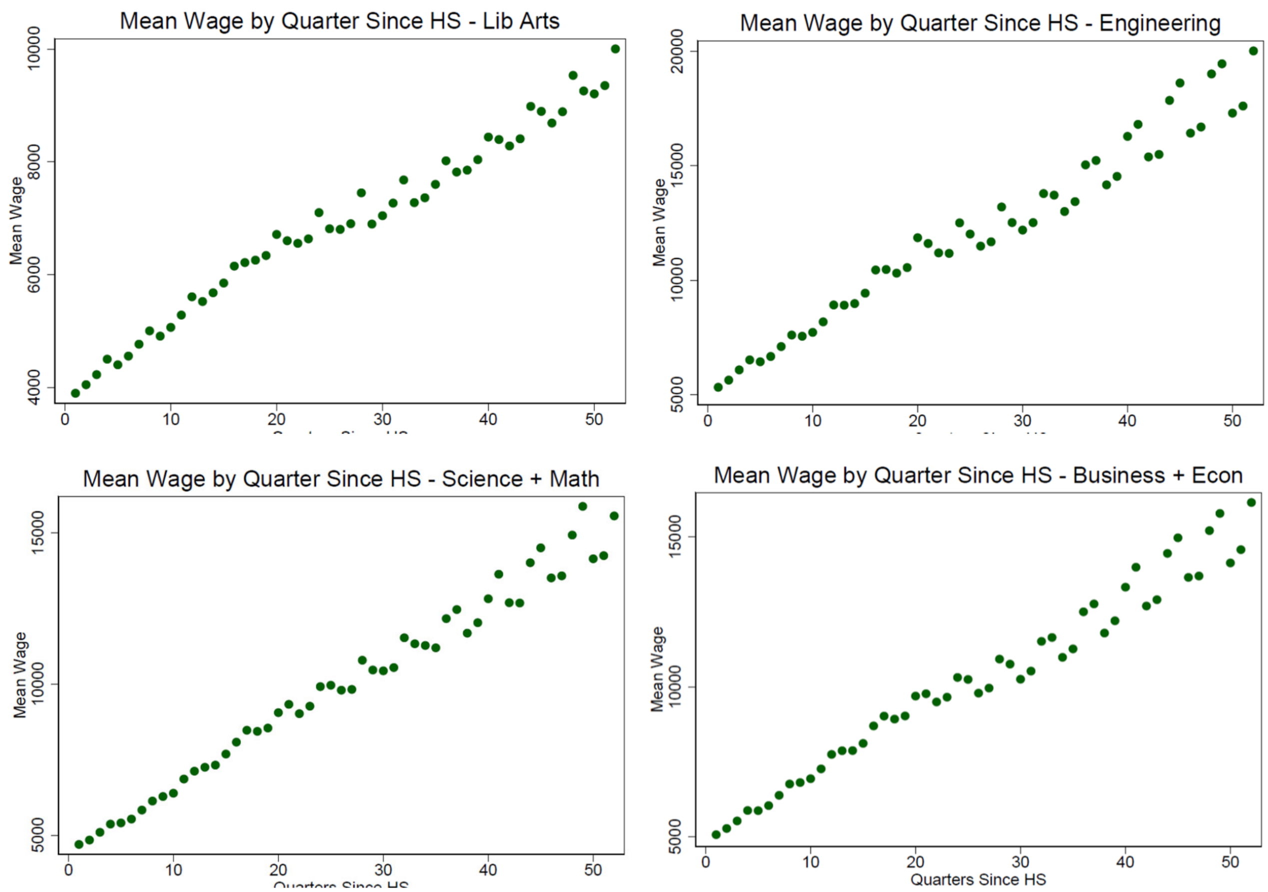
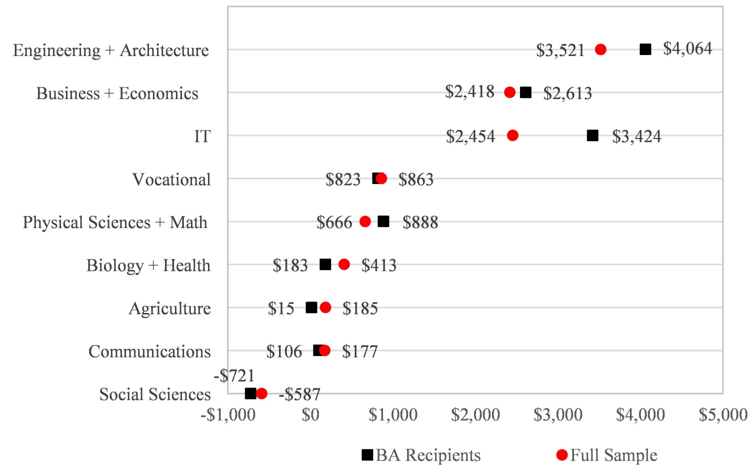
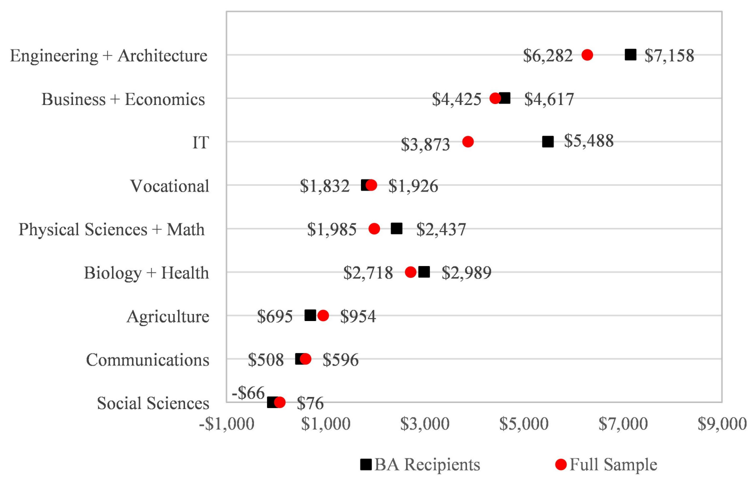


Figure A-2: The Return to College Majors by Years After High School and BA Completion - 4-year Students

(a) 6-10 Years Post-HS



(b) 11-15 Years Post-HS



(c) 16-20 Years Post-HS

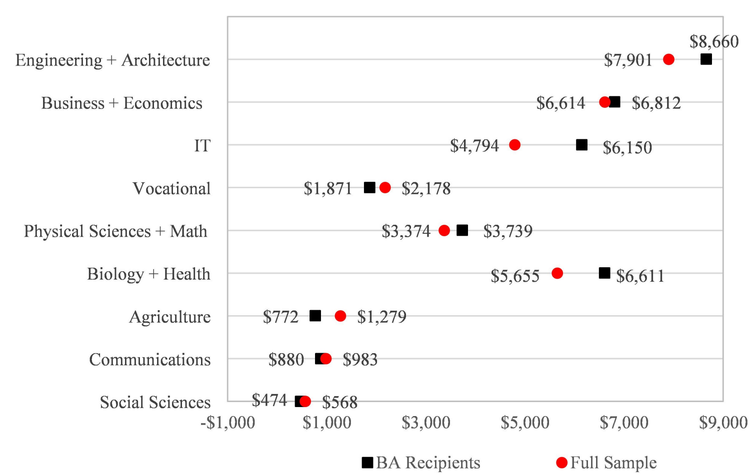
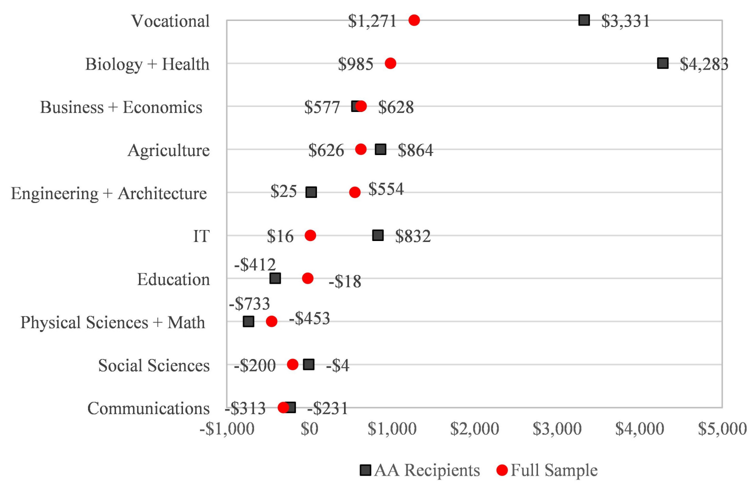
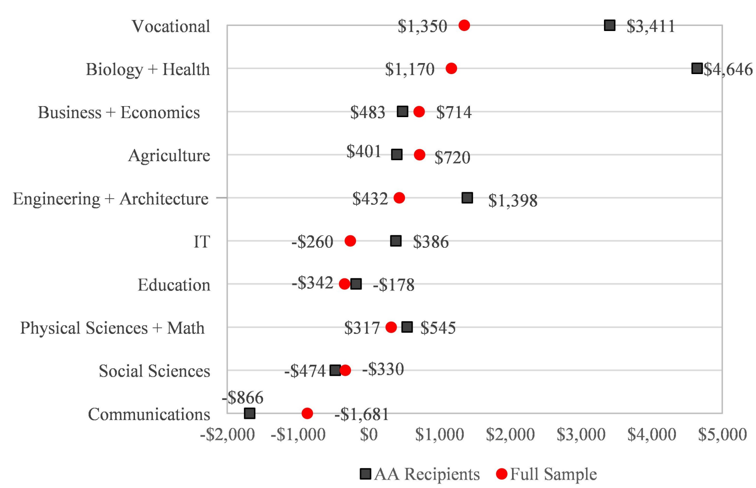


Figure A-3: The Return to College Majors by Years After High School and AA Completion - 2-year Students

(a) 6-10 Years Post-HS



(b) 11-15 Years Post-HS



(c) 16-20 Years Post-HS

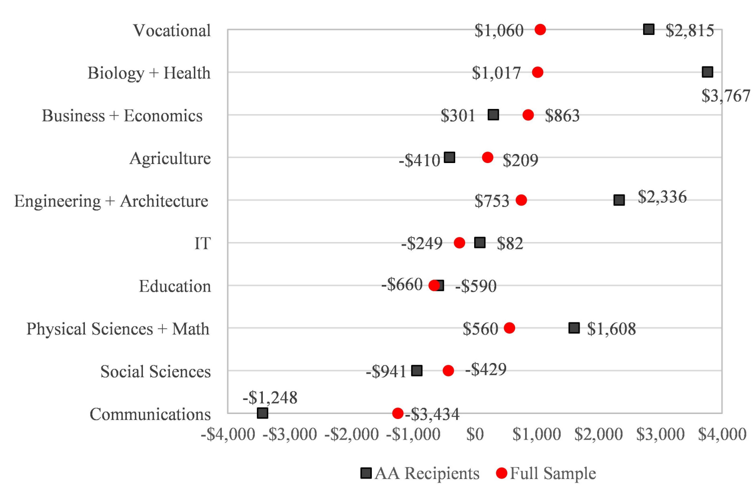
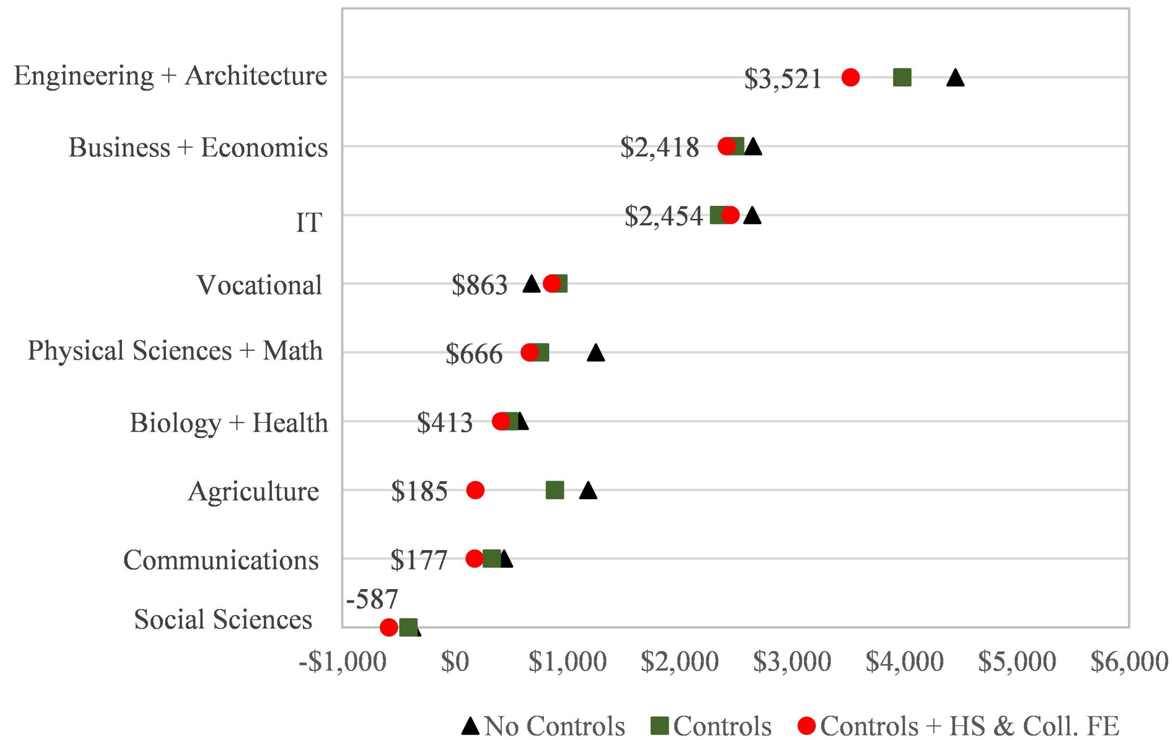


Figure A-4: The Return to College Majors by Years After High School, Early Years - 4-year Students

(a) 6-10 Years Post-HS



(b) 11-15 Years Post-HS

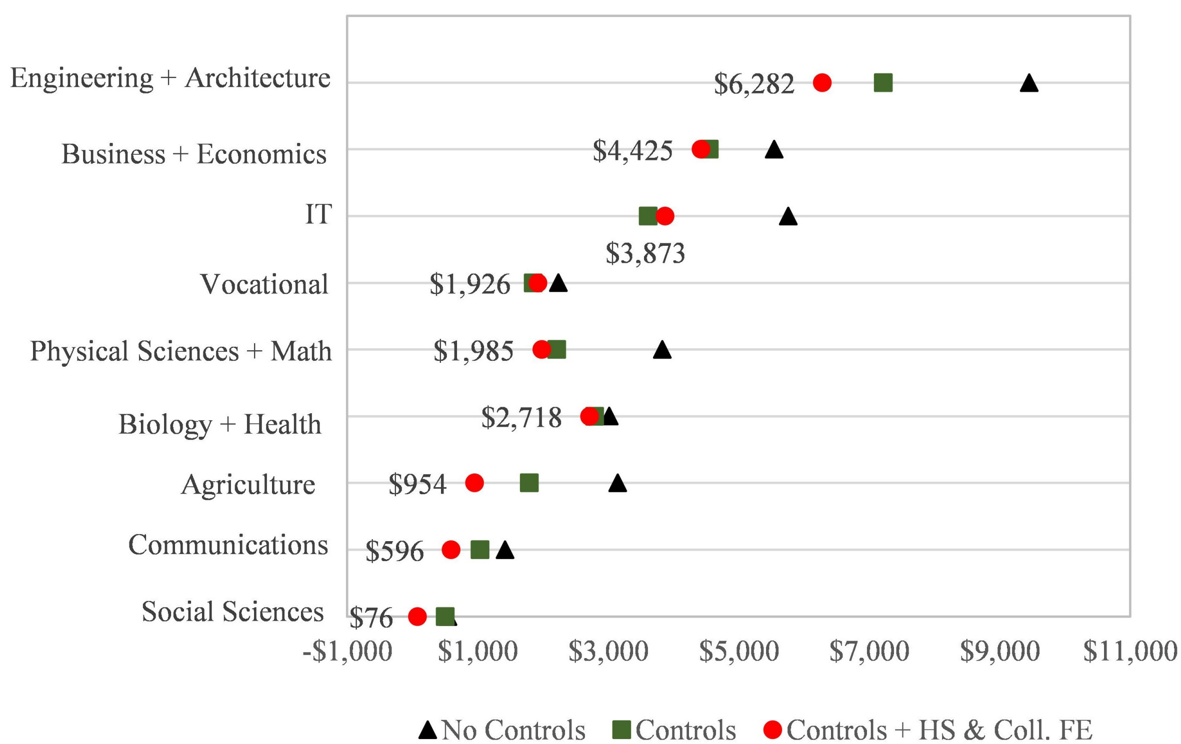
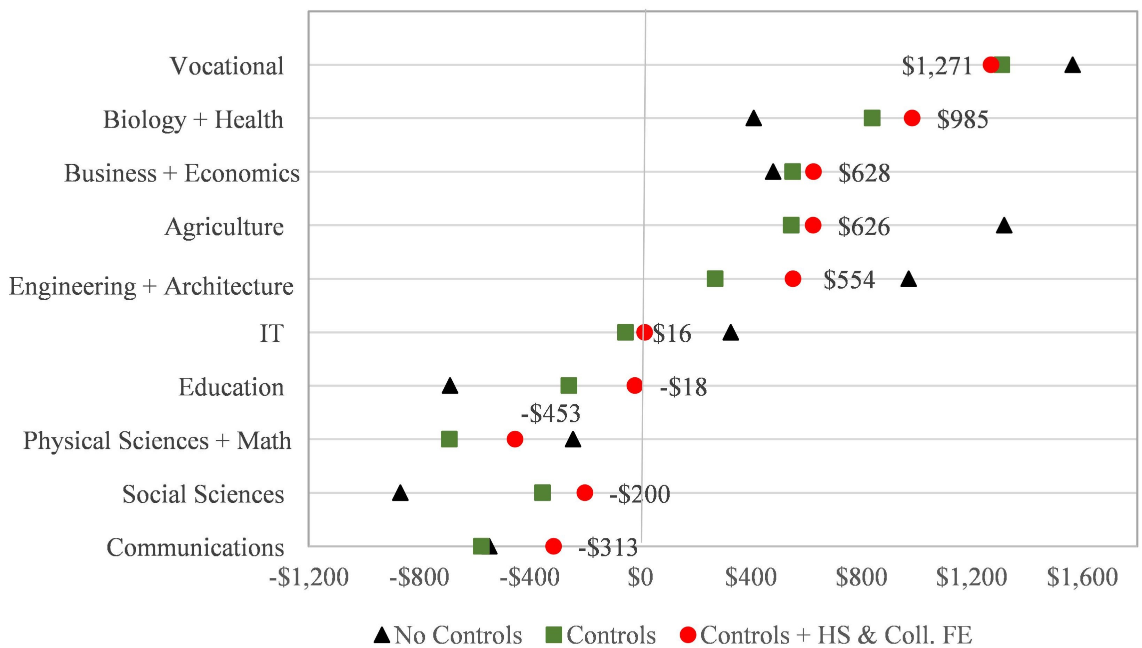


Figure A-5: The Return to College Majors by Years After High School, Early Years - 2-year Students

(a) 6-10 Years Post-HS



(b) 11-15 Years Post-HS

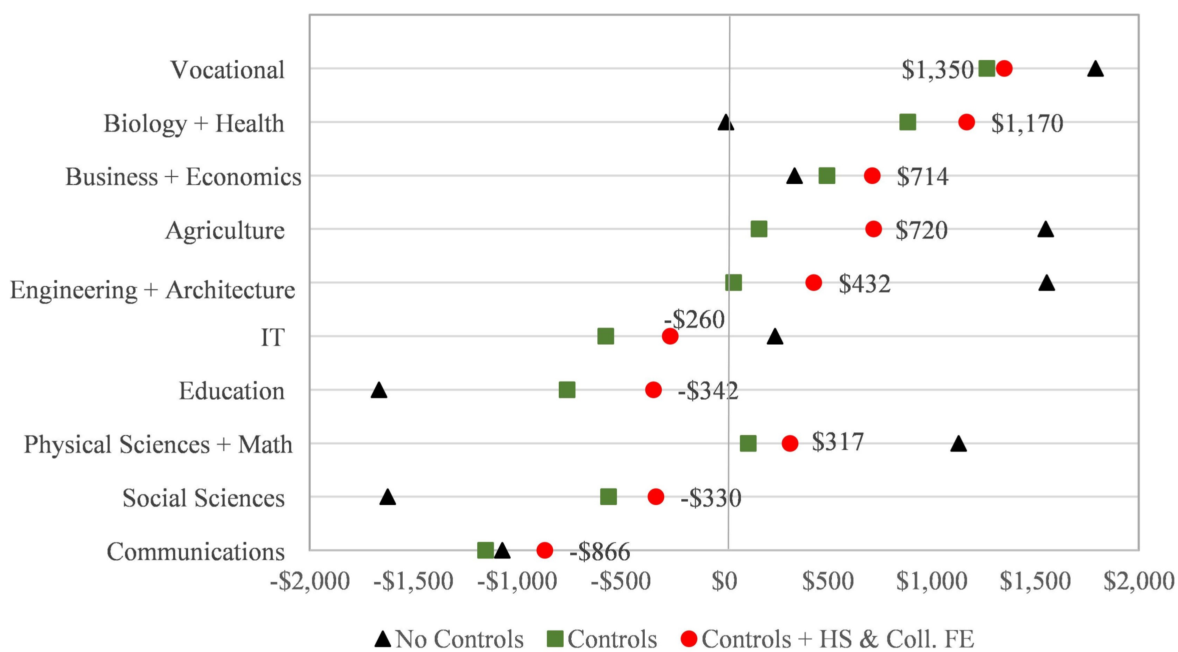
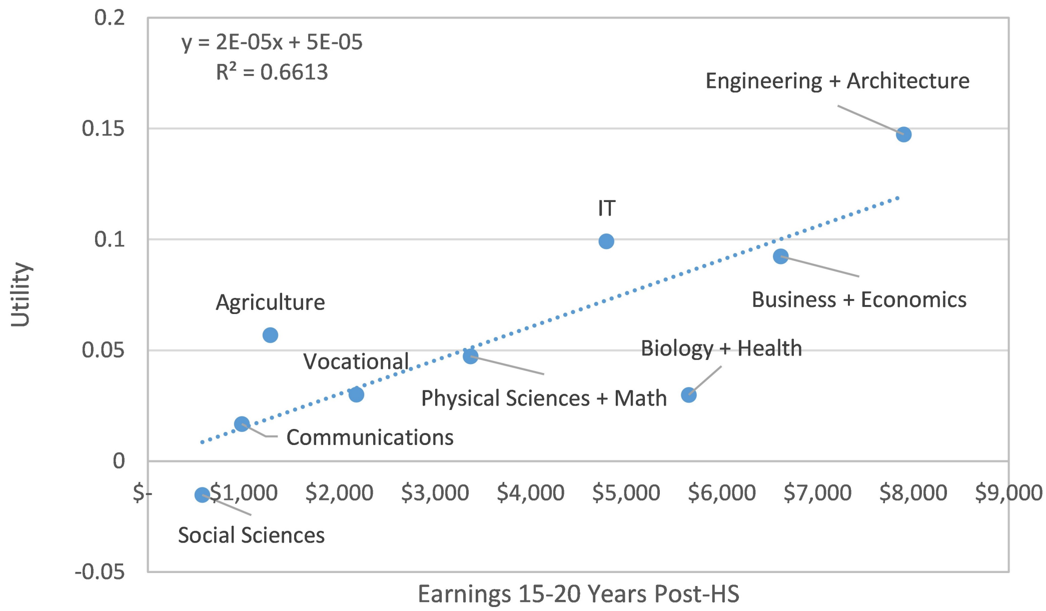
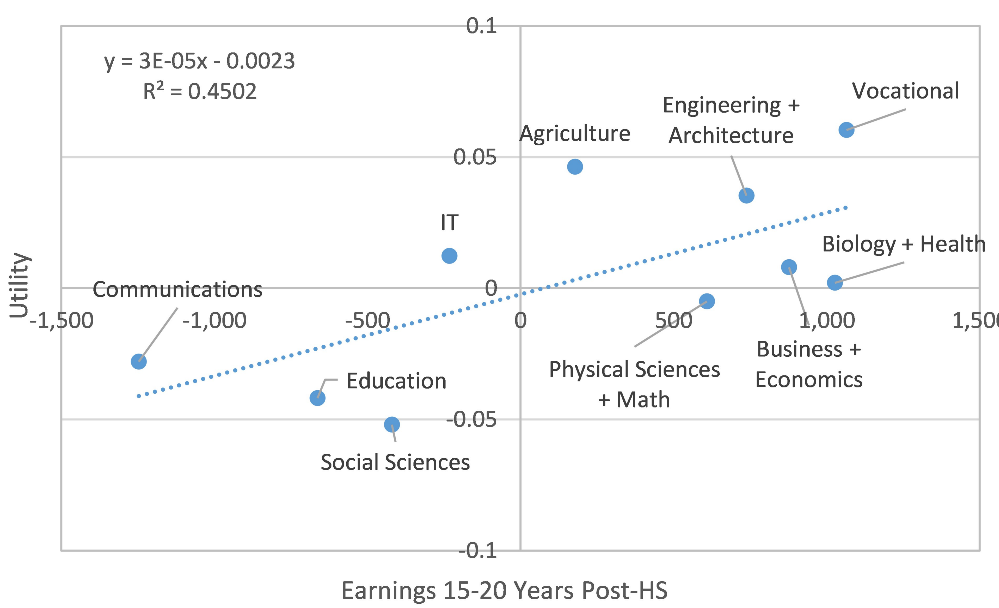


Figure A-6: The Relationship Between Earnings 16-20 Years Post-HS and Utility, $\gamma = 0.75$

(a) 4-year Students



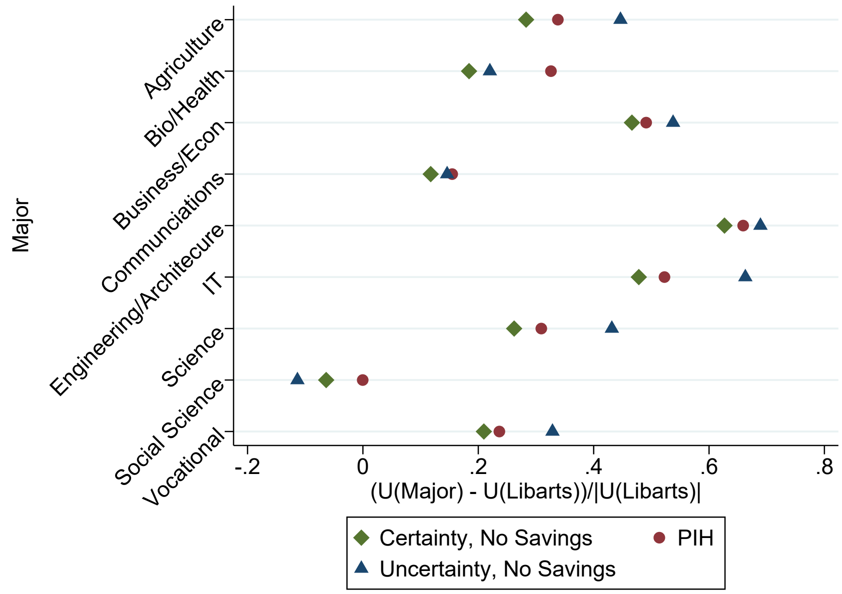
(b) 2-year Students



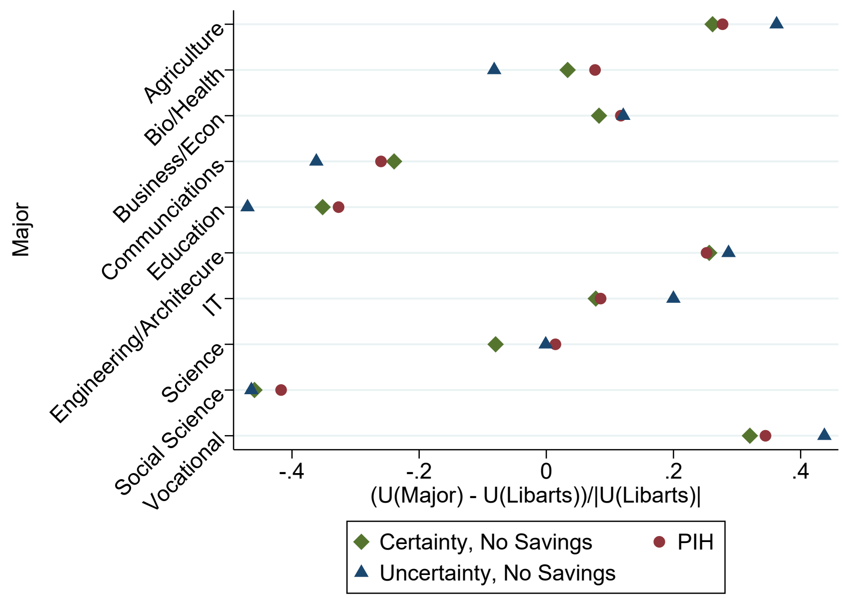
Notes: Earnings estimates include all controls and are for the period 16-20 years after HS graduation. The utility models use a quarterly discount rate of 0.99 and a coefficient of relative risk aversion of 0.75. Utility estimates using the "Uncertainty, no savings" model with earnings quantiles are shown in the figure. All earnings and utility estimates are relative to liberal arts.

Figure A-7: Utility Estimates by Earnings Model, Including Quantiles

(a) 4-year Students



(b) 2-year Students



Notes: Utility estimates are relative to liberal arts. All estimates shown use earnings estimates that include quantiles, a quarterly discount rate of 0.990, and a coefficient of relative risk aversion of 3.