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AVERAGE AND DISTRIBUTIONAL EFFECTS,
CAREER TRAJECTORIES, AND EARNINGS VARIABILITY

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

There is a growing body of research examining the labor market returns to college major, motivated by the large returns to skill in the labor market. Prior research has focused almost exclusively on mean effects and has paid little attention to the role of earnings growth and variability. Using linked administrative data from Texas on public K-12 students followed through college into the labor market, we find that the focus on mean differences mask four important features of the returns to college majors. First, majors are associated with varying earnings growth, which makes the returns sensitive to the experience distribution of the sample analyzed. Second, average earnings effects vary across workers; quantile treatment effect estimates show that mean effects mask considerable effect heterogeneity. Third, major choice affects earnings variability within workers over time. College major effects on earnings and variability are negatively correlated; high return majors also have more stable earnings. Finally, there is substantial variation in returns across specific majors within aggregate major groups and across institutions. This variation suggests that estimate of returns to college major are sensitive to how majors are aggregated and the composition of institutions in the sample.

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I. Introduction

The return to skill in the labor market is at historically high levels and continues to grow as the US industrial base shifts away from manufacturing and towards services. Even middle-class jobs require some postsecondary education, and substantial postsecondary education is almost necessary to access most high-paying professions. Consequently, the proportion of students enrolling in college has increased dramatically over the past half century: in 1970, 51.7% of recent high school graduates attended college, which rose to 66.2% by 2019. Total fall enrollment in US postsecondary institutions increased from 8.6 million to 19.6 million over this same period. The number of undergraduate degrees (associates and bachelors) awarded tripled, from about 1 million to 3 million.[1] The rise in postsecondary enrollment and completion has been driven, in part, by the high average return to collegiate training. However, the average return masks important heterogeneity across a number of dimensions (Lovenheim and Smith, forthcoming), one of the most important of which is college major or course of study.

Understanding the returns to college major is critical, as college major choice is the primary process through which individuals invest in specific forms of human capital (Hemelt et al. 2021). Even among those at the same institution and with similar pre-collegiate academic achievement, 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). Similar variation exists with respect to key academic outcomes, such as college completion, time to degree, and graduate school enrollment (Andrews, Imberman and Lovenheim 2017).

As the return to specific types of skill rises in the labor market (Autor 2014; Deming 2017), it is important to develop a more complete understanding of how major choice affects labor market outcomes. Furthermore, as the costs of attending college and student debt increase, providing information to students about the consequence of choosing different college majors can help them make better decisions that both potentially increase the return to their postsecondary investment and reduce the likelihood they will default on their loans. Students are

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

responsive to this type of information when making major choices (Wiswall and Zafar, 2015, 2021), which underscores the importance of providing them with accurate information about majors. Finally, understanding the returns to college major is relevant for policymakers and higher education administrators making resource allocation decisions. Providing more resources to higher-return majors can increase the aggregate return to college, and thus better understanding these returns can facilitate more efficient resource allocation within and across postsecondary institutions.

Prior research on the return to college majors focuses almost exclusively on mean effects of major at specific ages.[2] This paper sheds light on four dimensions of variation in the returns to major that have received little prior attention: 1) earnings growth with experience, 2) cross-sectional variation across workers, 3) within-worker variance in earnings, and 4) heterogeneity across finer distinctions of course of study and institutions.

The first type of variation is important because specific 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 is the ex-ante risk of choosing a major: the mean returns may be experienced by most students or reflect a wide range of outcomes that have important implications for workers' long-run well-being. The third source of variation reflects the within-worker variability of earnings at any point in time, which may differ across majors. Large 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). Furthermore, income volatility is substantially more harmful for Black households due to large racial differences in liquid wealth (Ganong et al, 2020). Whether variability magnifies or mitigates the welfare consequences of differences in earnings levels across majors also is an open question. The fourth source of variation is masked by aggregation decisions researchers make for empirical tractability, which typically entails combining different majors together within and across institutions. Aggregation may paint a misleading picture of the returns to completing a specific major at a given university.

To date, no research has examined in detail how major choice affects all of these factors within one consistent sample, and the literature is silent on the role of major aggregation. This

[2] Notable exceptions are Webber (2014, 2016), who estimate returns at multiple ages, albeit all from a cohort that finished college forty years ago, and Hershbein and Kearney (2014) and Hershbein, Harris and Kearney (2014), who examine major differences in earnings levels at different ages and earnings growth, respectively, without controls for selection.

lack of prior work is driven by the use of small samples (especially those that focus on the US as a whole) and employing annual earnings data that do not permit one to separate earnings growth from within-worker earnings variance. Our paper addresses two additional gaps in the literature as well. First, we examine the returns to majors among four-year (BA) and two-year (AA) students within the same context; prior work has analyzed one sector in isolation. Second, prior papers have focused predominantly on graduates, leaving open the question of what the return is for non-completers. We include non-completers so that estimates reflect the ex-ante information relevant to students at the time they make the major declaration decision, as this decision can have intermediary impacts on graduation likelihood. The importance of this is underscored by low completion rates at most US colleges (Bound, Lovenheim, and Turner 2010; Bound and Turner 2011; Denning et al. 2021).

We estimate the return to college majors using administrative data linking all Texas public K-12 students to higher education records among those attending a public postsecondary institution in-state and quarterly earnings records for all employees in Texas. Together, these data provide a sample size, a wealth of pre-collegiate information, and within-year earnings variation that are not available in any other US-based datasets. We estimate returns separately for those attending a four-year and a two-year college, aggregating majors into 10 groups plus undeclared.[3]

We employ selection on observables methods using rich pre-collegiate and collegiate data, and we estimate the return to each major relative to liberal arts (the excluded category). We account for pre-collegiate test scores and student demographics that have been used in some (but not all) prior studies of the returns to college major, but also include both high school by cohort and college by cohort fixed effects. Hence, we are comparing observationally-similar students 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 terms of their majors. As we show, these high school and college fixed effects have important impacts on the estimates, above and beyond test score and demographic controls. While selection on observables models embed the strong assumption that these observables are sufficient to account for all differences across students in

[3] These groups are engineering and architecture, business and economics, information technology, vocational, physical sciences and math, biology and health, agriculture, communications, social sciences, education (two-year degrees only, as Texas does not have a four-year education degree), and undeclared. Components of these groups can be found in Online Appendix Table A1.

potential labor market outcomes, we emphasize that our estimates are identified off of weaker assumptions than prior selection on observables analyses of the returns to college majors. There is a small literature, discussed below, that employs regression discontinuity (RD) models to study the returns to college major. However, there are few opportunities to use this method in the US across multiple fields and institutions, and estimating distributional effects with RD models is generally infeasible.

While we present a large number of results, there are several important findings that we highlight. First, we find that the returns to college major vary with experience in heterogeneous ways across majors and level. For example, the relative (to liberal arts) return to a four-year biology and health or economics and business degree doubles or triples after two decades, while relative returns to agriculture, communications, and social sciences decline substantially with experience. Quarterly returns vary from $664 in social sciences to $8,016 in engineering and architecture 16-20 years after high school. Among two-year students, the returns to almost all degrees are positive relative to liberal arts 6-10 years after high school, but by 16-20 years after high school, earnings for liberal arts degrees are in the middle. These results underscore the high return to a liberal arts AA degree in the long-run relative to the short-run.

The results further point to important differences in the variance of returns both cross-sectionally and within-worker. Quantile treatment effect estimates (DiNardo, Fortin, and Lemieux 1996; Firpo 2007) indicate much variation across majors in how they influence the distribution of earnings, with some majors shifting the earnings distribution relatively uniformly and others generating much larger effects at the top of the distribution. This suggests the mean effects embed substantial (and differential) ex-ante risk for students. Further, college majors have a modest effect on the within-worker variance in earnings, measured by the coefficient of variation (CV) 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. In both the two-year and four-year sectors, the mean earnings effect is negatively correlated with the effect on the coefficient of variation. High returns majors also have lower earnings variability, making them even more desirable to students.

Finally, we show that while aggregate major groupings are informative, there is substantial heterogeneity in returns across different Classification of Instructional Programs fourdigit (CIP-4) categories.[4] There is even more variation in the return to aggregate major categories across institutions, which is suggestive of large program-specific effects. These results indicate that future research should engage carefully with aggregation across majors and institutions; variation in findings across previous studies could be due to different aggregation procedures and differences in the set of institutions in the analysis sample.

Our paper contributes to the growing literature on the returns to college major, which we discuss in the next section, by moving beyond an analysis of mean effects at specific ages. We show 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 the role of aggregation. We do so using rich administrative data that allows us to control extensively for selection into different majors. 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.

II. Prior Work on College Major Choice

A growing body of research examines the return to college major. Reviews by Altonji, Blom, and Meghir (2012), Altonji, Arcidiacono, and Maurel (2016), and Lovenheim and Smith (forthcoming) summarize this literature in detail. Here, we discuss the broad approaches taken in prior research and how our paper contributes to this work.

Most of the prior literature focuses on the relationship between four-year college majors and mean earnings. Several studies have shown a strong correlation between college major and subsequent average earnings, with the general finding that business, engineering, and physical science graduates earn more than students from other fields (James et al., 1989; Hammermesh and Donald, 2008, Carnevale and Cheah, 2013; Hershbein and Kearney, 2014; Carnevale, Cheah, and Hanson, 2015). The central concern with the correlational evidence is that students sort across majors based on their own knowledge of their ability and preferences that researchers cannot observe. Turner and Bowen (1999) and Arcidiacono (2004) show that students who major in technical areas, such as economics and STEM fields, have higher pre-collegiate math

[4] The CIP is provided by the US Department of Education and is intended to group fields with similar academic foci together.

achievement. Math ability is likely to have independent effects on labor market outcomes. Without accounting for the differences across students in earnings potential, one cannot interpret earnings differences across majors as causal.

Researchers have primarily used four approaches to overcome these selection issues.[5] The first is to control for any pre-collegiate academic achievement and demographic differences to account for underlying skill differences across students that are correlated with major choice.[6] These studies use national surveys to estimate returns to major and often account for many observed pre-collegiate characteristics of students. The set of characteristics on which they focus varies across studies, and none are able to control for high school and college fixed effects. Furthermore, the relatively small sample sizes in these datasets require substantial aggregation. A second approach to addressing this selection problem is to explicitly estimate a model of the major selection process and outcomes simultaneously, as typified by the dynamic structural model of Arcidiacono (2004). He finds that the returns to college are highest for business and natural science majors.

Third, a few recent studies exploit major admission cutoff rules in a regression discontinuity framework (Hastings, Nielson and Zimmerman 2013; Kirkebøen, Leuven and Mogstad, 2016; Andrews, Imberman and Lovenheim 2017; Bleemer and Mehta 2022). This approach is motivated by concerns that even a rich set of controls may be insufficient to fully account for selection into majors. This research tells a remarkably consistent story of large causal effects of major choices on earnings. The first two studies focus on international contexts where there are admission cutoffs based on high school performance metrics. The second two studies estimate effects in the US using GPA cutoffs for admission to a single major (business and economics, respectively). This highlights the difficulty of using this method in the US context, as binding cutoffs for major access are confined to a small number of fields. These analyses also focus exclusively on four-year degrees.

A fourth approach, favored in analysis of two-year schools, is to utilize the fact that many students in associates degree programs work prior to enrollment. This allows researchers to compare earnings before and after enrollment using individual fixed-effects. Jepsen, Troske and

[5] Anelli (2018) is unique in employing an instrumental variables strategy that uses faculty recommendations to instrument for major choice in Milan, Italy, although he also uses a selection-on-observable strategy as we do.
[6] See Altonji, Blom, and Meghir (2012) and Altonji, Arcidiacono, and Maurel (2016) for a review of selection on observables studies.

Coomes (2014) and Stevens, Kurlaender and Grosz (2019) employ this method with data from Kentucky and California, respectively. They 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.

We make several contributions to this literature. First, we show variation in returns to major as workers gain experience using rich controls and a large sample that spans both the two-year and four-year sectors. 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) or into ages in the early- and mid-thirties (Arcidiacono, 2004; Andrews, Imberman, and Lovenheim, 2017). Heterogeneity in the earnings paths associated with different college majors makes it challenging to compare results across studies. Prior work that does show variation in the returns to major over the life course typically has limited controls for selection.[7] For instance, Hershbein and Kearney (2014) show median lifetime earnings and earnings trajectories by Bachelor's Degree major in the ACS. Webber (2014, 2016) simulates the lifetime returns to different majors by combining data from the NLSY and the ACS, finding differential growth in earnings over the early career. Martin (2021) combines the ACS, the National Survey of College Graduates (NSCG), and the Longitudinal Employer Household Dynamics database to classify majors as "specific" or "broad" based on how closely tied they are to specific occupations. She shows that the return to specific majors is higher early in the career, but the gap shrinks over time as the latter increasingly switch jobs. Our paper extends this literature by directly examining how returns to major in both the 2-year and 4-year sectors vary with potential experience, controlling for selection based on an extensive set of student observables.

Second, we move beyond the examination of mean effects by estimating distributional effects and variability, which capture two important dimensions of risk. None of the papers described above examine distributional effects closely, and mean effects may be a poor reflection of earnings for the typical student. For example, a major with high mean earnings can either reflect few workers having very high earnings and most workers having lower earnings, or it can

[7] Kim, Tamborini, and Sakamoto (2015) also examine how the return to postsecondary education varies with experience, but they do not examine the role of college major. Deming and Noray (2020) use job opening data to show that majors linked to occupations with rapid technological change experience high returns early in the career that fade over time as workers' skills become more obsolete.

reflect most workers experiencing modestly high earnings. If high mean earnings returns come with substantial risk, then it reduces the long-run benefits of individual majors. Prior work provides indirect evidence for the importance of effect heterogeneity. Andrews, Li and Lovenheim (2016) report evidence of substantial cross-worker variability of college quality effects. For example, the return to graduating from UT-Austin relative to a non-flagship public university in Texas ranges from 3.4% to 31.6%. However, the cross-worker returns at Texas A&M are remarkably stable. The authors provide suggestive evidence that major differences across the institutions can explain these findings. Leighton and Speer (2020) document differences in returns to majors across occupation, and Schanzenbach, Nunn, and Nantz (2017) investigate raw differences in median earnings within major fields across occupations. None of these studies directly identifies how college majors shift the entire distribution of earnings, which is one of the contributions of our paper.

Prior work also does not address the potential for major choice to alter within-year earnings variability for individuals, perhaps due to the use of annual data.[8] Such fluctuations in earnings can be harmful to families if they lack full access to credit and "buffer stock" savings. Certain majors may be associated with unexpected low earnings periods within or across years. If individuals are risk-averse or credit constrained, such variation can reduce well-being (Zeldes 1989; Stephens 2003; Chetty 2008; Ganong et al, 2020). For example, Dillon (2018) finds that people are willing to enter occupations with significantly lower salaries to avoid earnings variability due to risk aversion. Since students at two-year schools and less-selective four-year schools are more likely to come from lower-income and disadvantaged backgrounds, within-year variance in earnings may be of particular concern for them.

Our final contribution is to address aggregation issues that have received little attention in prior research. Because of sample size concerns and the large number of majors, previous studies usually aggregate majors into broad areas, such as "STEM" or "social sciences." Each study aggregates majors differently in ways that often are difficult to observe. Variation in returns to different specific majors within each group will generate differences in results across studies. We are the first to assess the empirical relevance of this source of variation. Relatedly, prior research has largely ignored the potential for major returns to vary across different institutions (i.e.,

[8] Delaney and Deveraux (2019) exploit education expansions and find that more education lowers earnings volatility. They do not examine college major effects, however.

programs). Kirkeboen, Leuven, and Mogstad (2016) find little evidence in Norway of program-specific effects, though Britton et al (2021) do so in the UK. Postsecondary systems differ considerably across countries, however, and our results show evidence of large variation in returns to major across institutions. These findings suggest that aggregation issues in the returns to major literature are not innocuous and highlight the importance of considering these issues carefully in future work.

III. 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 secondary school through college and into the workforce, provided individuals remain in Texas and attend public schools.

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 such as race/ethnicity, gender, whether the student is eligible for free or reduced-price lunch, whether the student is at risk of dropping out, and enrollment in gifted and talented programs.

This sample of high school graduates is merged with data from the THECB, which contain detailed information about college enrollment in each semester, college major(s) in each semester, and whether and when a degree was earned from each institution. These data contain all students who enroll (completers and non-completers) in a public postsecondary institution in Texas, including both two-year and four-year institutions. 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. How to classify students by sector and major is not straight-forward, given the diversity of pathways students take through college (Andrews, Li, Lovenheim, 2016). We aim to capture the postsecondary experience that will be most salient to employers when students end their education. 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 that earn a Bachelor's degree 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 BA. Students that earned an Associate's degree (but no Bachelors) 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 than their four-year enrollment that did not lead to a credential. Students that did not earn a BA or AA degree are assigned to the sector of their last enrollment, regardless of where they started. This ensures we are focusing on the most salient and recent degree or enrollment information that employers may see and that likely determines the skills workers bring to the labor market.

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 their specific CIP-4 major: agriculture, communications, IT, vocational, engineering and architecture, biology and health, physical sciences and math, social sciences (excluding economics), business and economics, and undeclared.[9] Two-year students may also be an education major; no such major is offered by Texas public four-year colleges. No students with an "undeclared" major have a college degree, and many students with a declared major do not complete a degree.

Labor market outcomes are constructed from quarterly earnings records through 2017 for each student who works in Texas, except for those who work for the Federal Government or who 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, 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). There is little evidence in our sample of differential attrition from the earnings sample by college major (see Online Appendix Table A-2.)

[9] Appendix Table A-1 lists the detailed majors included in each broad major category. Majors are grouped based on both 2- and 4-digit CIP codes.

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. While addressing out-migration bias, this approach will tend to ignore any impacts of college major on the likelihood of employment immediately after college or towards the end of our analysis window. 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 enrollment to a specific major.[10] Finally, we only include earnings observations at least 6 years after high school graduation. Earnings are converted to 2016 dollars, and we assign zero earnings to those with no earnings in a quarter within their in-state employment window. For computational tractability, we collapse the included quarterly observations to compute the average earnings in each experience range (6-10, 11-15, 16-20 years post-high school). The sample sizes reported in the tables thus reflect the number of unique individuals, not the number of quarterly observations.

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. Reflecting national trends, the college-going sample is predominantly female. There also is sizable representation among Hispanic, African American, and Asian students. The most prevalent major 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 are double majors. For these students, we code them as majoring in both subjects.

[10] Unfortunately, we are only able to observe enrollment in Texas public institutions and thus periods when people are enrolled in private or out-of-state institutions are included in the earnings data. This would bias our estimates only to the extent that majors differentially sort to such institutions for graduate school.

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 at a point in time is the absolute value of the deviation of actual (Y_{it}) from predicted ($\hat{Y}_{it}$) quarterly earnings, divided by the predicted value. This is the coefficient of variation, $\widehat{CV}_{it} = \frac{abs(Y_{it} - \hat{Y}_{it})}{\hat{Y}_{it}}$, which can be interpreted like a standard deviation. Informally, the mean of this measure quantifies the average quarterly deviation from what individuals are "expected" to earn. Those with large year-to-year or quarter-to-quarter fluctuations will have high levels of variability and a larger CV. A negative effect on the CV indicates that a major exhibits lower earnings variability than the base major.

To construct the coefficient of variation, we 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 category ($\tilde{Y}_{it}$):

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

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 in year 5 after high school (the first year 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.[11] To assess the robustness of our results to alternative ways of predicting earnings, we also use a 4-quarter and 8-quarter moving average (MA) ending with the focal quarter. For example, if the observation is

[11] We are restricted to linear individual growth profiles due to computational tractability. Nonetheless, Online 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.

Q1 2010, we would predict earnings sing quarters 2 to 4 of 2009 and quarter 1 of 2010 for the 4-quarter MA and would use quarters 2-4 of 2008, quarters 1-4 of 2009 and quarter 1 of 2010 for the 8-quarter MA.

IV. Empirical Methodology

a. Linear Model

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

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

where Y_{iscjk} is an outcome for individual *i* (e.g. mean earnings in a time period, coefficient of variation, etc.), 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. 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 high school level, reflecting the correlation of outcomes across students at the same 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 11th 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, and being economically disadvantaged.

The test score and demographic controls are similar to what is used in the most high-quality prior selection-on-observables studies, although these typically do not include relative rank controls. Our large sample sizes also allow for two types of detailed fixed effects: high school-by-graduating cohort and college-by-cohort.[12] 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, there is strong sorting of students into different colleges, and so, there likely are smaller differences in unobservables across students within the same college and cohort than there are 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 prior literature. While we are unable to test the identifying assumption of no selection on unobservables conditional on the included controls, we emphasize that this is a weaker assumption in our context than in prior research using this method because of our richer control set. We additionally demonstrate the sensitivity of results to the inclusion of this richer 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:

[12] We often refer to these as high school and college fixed effects for the sake of brevity. In all cases these fixed effects are for high school by cohort and college by cohort.

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

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 construct weights:

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

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.[13] 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. The reweighting approach relaxes the linearity assumption in OLS models, but both methods 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.[14] Under the selection on observables assumptions, 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.[15] As discussed in Heckman, Smith, and Clements (1997), the treatment effect on the distribution of earnings is necessary for conducting welfare calculations of treatment effects.

V. Results

a. Mean Earnings Effects of College Major and Earnings Trajectories

[13] This method is akin to the aggregate decomposition described in Fortin, Lemieux, and Firpo (2011).
[14] One subtle difference is that by estimating (3) separately for each non-liberal arts major, we permit the individual controls to have different coefficients for each non-liberal arts major. Our approach to estimate mean differences with equation (2) constrains the coefficients to be equal across majors.
[15] This differs from the distribution of treatment effects. To estimate the distribution of treatment effects with this method one needs a rank invariance assumption, which is 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 employ.

Panel (a) of Figure 1 presents the estimates of θ_k from equation (2), combining observations 16-20 years after completing high school among four-year students.[16] The black triangles show estimates without controls but with cohort fixed effects, the green squares show the estimates that include the student-level observables discussed in Section IV, and the red circles present the 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 for all of these models are shown in Appendix Table A-5.[17] 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.[18] Engineering and architecture has the highest returns at $8,016 per quarter relative to liberal arts, with business and economics ($6,742), biology and health ($5,747), and IT ($4,915) also experiencing high relative returns. Average quarterly earnings in this sample is $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 returns followed by social sciences ($664), communications ($1,083), and agriculture ($1,374).

This figure also shows the importance of controls for selection. 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 $14,102 to $8,016, 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. Conversely, the estimates for social sciences, vocational, and communications are less sensitive

[16] Since students tend to finish school in late spring, we start our timeline from the third quarter rather than the first quarter of the calendar year.
[17] Because we use average individual earnings that qualify for sample inclusion and that are in the specified potential experience range, the number of observations in the tables reflect the number of individuals rather than the number of quarterly earnings observations.
[18] Figures 1 and 2 do not show the estimates for "undeclared," since this is a difficult major to interpret. All undeclared majors drop out of college before obtaining a degree, which is not the case for the other majors. This group is included when we estimate equation (2), and results for this "major" are shown in Online Appendix Tables A-4 and A-5.

and in some cases are insensitive 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. 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 extensive set of observables in the “controls” models. As shown in Online Appendix Table A-5, these fixed effects are more important for more experienced workers, suggesting that some of the residual selection bias is expressed in the form of different endogenous rates of earnings growth. Our results 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. Several fields exhibit substantial growth in returns over time: biology and health returns increase from \$1,295 to \$5,747 in the two decades after high school, engineering and architecture increases from \$4,462 to \$8,016, physical sciences and math increases from \$1,544 to \$3,464, and business and economics increases from \$3,372 to \$6,742. It is possible that some of this growth reflects investments in graduate school and subsequent sorting of these students into high-paying professions.[19] To the extent that attending graduate school and joining one of these professions is facilitated by one’s college major, it is appropriate to include the returns to graduate school as a part of the returns to majoring in a given field.

In contrast to growth over time in several fields, the relative returns to agriculture, communications, and social sciences all decline with experience. This implies that liberal arts students start to catch up to those in these fields, while they fall further behind those in the fields listed in the prior paragraph. These estimates never become negative, however, and so liberal arts remains the lowest earning field up to twenty years after high school. These findings are very important in showing that it matters when in the career earnings are observed for accurately identifying the returns to different majors. Relative growth in some fields and declines in others

[19] 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 (forthcoming) review the returns to graduate school literature.

cause rank switching as workers gain experience. This will lead to heterogeneity in findings across papers based only on the experience composition of the sample.

Figure 2 presents analogous estimates among two-year students.[20] Similar heterogeneity is evident as in the four-year sector, although the specific patterns across majors differ and the gaps are smaller. This highlights the value of examining the two levels separately. Turning to Panel (a) we see that sixteen to twenty years after high school, the highest earnings are found among vocational ($931) and biology and health ($868) majors, relative to liberal arts majors. Communications, education, and social sciences all exhibit negative relative returns of over -$500, with the penalty for communications being particularly large at -$1,355. Average quarterly earnings among 2-year students is $11,627 16-20 years after high school, so these effects are sizable when compared to the mean. Liberal arts majors at 2-year colleges thus end up approximately in the middle of other majors.

As in the four-year sector, panel (a) of Figure 2 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 biology and health, business and economics, education, and social sciences, accounting for controls lead to sizable increases in the returns. This is evidence of endogenous selection into these majors. However, as with the results for four-year students, the effect of the controls does not vary much across experience groups, and 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 substantially with experience, as demonstrated in panel (b). Relative to liberal arts, the returns for vocational and biology & health are even larger in the years immediately after college, but these diminish somewhat over longer time horizons. On the other hand, the earnings advantage of liberal arts majors relative to communications and social sciences grows with experience. The positive return to vocational degrees aligns with prior literature showing that high average returns to vocational two-year degrees (Lovenheim and Smith, forthcoming), particularly in the short-run.

Figures 1 and 2 show large changes in the returns to different majors as workers gain experience. We now present estimates that more directly examine how college major affects the

[20] Appendix Table A-6 provides the coefficients and standard errors shown in Figure 2 along with estimates that include different controls in each experience range.

trajectory of earnings. We estimate a version of equation (2) in which we interact each major category with indicator variables for every year of potential experience from 6 through 19 years after high school.[21] These results show the relationship between college major and the trajectory of earnings and provide some insight as to whether returns stabilize towards the end of our sample period.

Figure 3 presents these estimates for four-year students and Figure 4 presents them for two-year students. The results align closely with those in Figures 1 and 2. In Figure 3, the returns stabilize after 10 years of potential experience for most major groups. The main exceptions to this pattern are for engineering and architecture, biology and health, and business and economics. The returns to these majors continue to increase strongly through the end of our sample period, suggesting that measurement even 15-19 years after high school (typically ages 33 through 37) provides a lower-bound of the lifetime earnings premiums. Returns to physical science and math exhibit a smaller increase through the end of the observation period as well. Vocational returns decline with potential experience, however the rate of decrease is modest. These results reinforce the conclusion from Figure 1 that it is important to account for earnings trajectories and the age of the sample when examining the returns to majors. Returns change considerably and differentially as workers gain experience, especially during the first 10 years. For some majors, the slopes in the 16-19 year post HS period are non-trivial, suggesting that relative returns will continue to change as workers reach the peak of their careers.

Analogous estimates for two-year students are shown in Figure 4. There is far less variation in growth across majors than was evident in the four-year sector. Most estimates trend downward over time, which underscores the long-run relative value of a liberal arts major in the two-year sector. Vocational graduates, who have some of the highest earnings premiums in the 2-year sector, experience a steep drop in earnings relative to liberal arts after 10 years.

The results presented thus far show that there is a wide variation in the returns to major that differ across the two-year and four-year sectors, that are differentially sensitive to the inclusion of controls, and that exhibit different rates of growth over time as workers gain experience. In particular, these results underscore the importance of the age or experience composition of the sample in estimates of the return to major, which has received little attention

[21] We cut off this analysis at 19 instead of 20 as the number of observations 20 years after high school are too small to generate precise estimates.

in prior work.[22] We now turn to an examination of the variance in returns, first focusing on cross-worker variance in average returns and then within-worker variation in earnings.

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.[23]

We estimate quantile treatment effects (QTE) of each major relative to liberal arts. These 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 5 shows QTE estimates for the six largest fields of study among four-year students. Results for other fields can be found in Appendix Figure A-4. The outcome is average person-level mean quarterly earnings across all years and experience levels included in our sample. In each panel, we plot the difference at each percentile of the earnings distribution between the focal major and liberal arts majors, the latter reweighted to observably match the focal major distribution as described in equations (3) and (4). The solid curve represents the QTE estimate, and the dots show the 95% confidence intervals that are calculated using a block bootstrap at the high school level.

Generally, the mean differences across fields do a poor job of capturing the earnings consequences of major choice for most students. The slope of the QTE curves vary considerably across majors. Engineering & architecture, business & economics, and biology & health, all

[22] 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 looking only at degree recipients, the relative ordering of fields is quite similar to our preferred sample that also includes non-completers. Furthermore, these figures demonstrate the importance of experience, since the completer estimates are often smaller in earlier periods and then grow substantially over time.

[23] 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.

exhibit strongly upward sloping QTEs. This means that these majors shift out earnings much more at the top of the distribution than at the bottom (relative to liberal arts). Even at the bottom of the distribution, none of the estimates is negative, but the largest returns to these majors flow to those at the top of the distribution. Thus there is considerable ex-ante risk associated with the mean returns shown above, as these averages reflect much smaller returns for those low in the earnings distribution and higher returns among those at the top of the distribution.

The ex-ante risk is even larger among communications and social science majors. For these majors, only the top of the earnings distribution shifts out. 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. The mean effects present a misleading picture of the earnings returns to these majors.

Figure 6 presents QTE estimates for the six largest fields among 2-year students. The remaining fields are provided in Appendix Figure A-5. 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 social science and education majors. This means that the earnings penalties associated with these majors relative to liberal arts are particularly large among higher earners. The QTEs are relatively flat among, business & economics, IT, and biology & health majors. While we see upward slopes on the QTE estimates for these majors, the range of the returns across the distribution is small, differing by less than $1000 in all cases. Hence, for these majors, the average estimates are representative of what students can expect to earn. Of the largest fields, only vocational majors show a large positive gradient 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 reflect ex-ante risk on the part of the student considering a given major.

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 (3) using the coefficient of variation measures described in Section III.b.

Table 2 presents estimates that vary with respect to the controls used and the earnings prediction model. Odd-numbered columns include only cohort fixed effects, while even-numbered columns include all controls and fixed effects. Columns (1)-(2) are our preferred estimates and use individual-specific linear slopes and intercepts to predict earnings in each quarter. Subsequent columns use a 4- and 8-quarter moving averages ending in the focal quarter.

We focus on the estimates in column (2), which are from our preferred model and include all controls. The point estimates are universally negative and are statistically different from zero at the 5% level, indicating that earnings are less variable relative to liberal arts majors. The effects range from -0.038 for social sciences to -0.150 for business & economics. The interpretation of these estimates is that the average deviation from trend is 3.8% lower for social sciences and 15.0% lower for business & economics relative to liberal arts. These estimates point to liberal arts majors experiencing more within-person variability than other majors. Estimates are not sensitive to the inclusion of controls, but they are somewhat attenuated when using moving averages to predict earnings. This is unsurprising, as these are more flexible than the individual linear predictions. Hence, these prediction models soak up more of the earnings variation within individuals over time. The estimates in column (4) range from –0.017 (social science) to -0.120 (IT) and continue to be statistically significant at the 5 percent level. In column (6) that reports results using an 8 quarter moving average, the estimates range from -0.021 (social sciences) to -0.182 (IT and Business). All of these estimates are significantly different from zero at the 5 percent level.

Taken together, these results suggest that these majors reduce earnings variability modestly relative to liberal arts. That the estimates are smaller when using the more flexible prediction model does not mean these estimates are more credible. It could be that the moving averages are overly-smoothed and incorporate variation in the prediction that is actually unexplained variance from the point of view of the worker. While we favor the linear prediction estimates, we present a range of results because there is no direction from the literature on which of these prediction models is more desirable. Although the point estimates vary across models, the qualitative conclusions do not. Across all of the estimates in Table 2, the results suggest that all major fields are less variable than liberal arts, with variability gaps of up to 20%. Hence, within-person uncertainty and risk due to college major choice likely have substantial effects on individual well-being.

Effects of college major on the coefficient of variation among 2-year students are shown in Table 3. The estimates in column (2) are much smaller than their counterparts in the four-year sector, ranging from -0.097 (undeclared) to 0.003 (physical sciences and math). All but two of the estimates are significant at the 5% level, and only the estimate for physical sciences and math is positive (but not significant at even the 10% level). The moving average models produce comparable effects, ranging from -0.079 (undeclared) to 0.004 (physical sciences and math) in column (4) and from -0.117 (undeclared) to 0.016 (physical sciences and math) in column (6). None of the positive estimates are statistically significant at conventional levels.

The CV point estimates generally are smaller for two-year students than for four-year students, suggesting fewer differences across major in terms of earnings variability. Overall, we find that earnings variability differences from two-year major choice are, at most half the size of those from four-year major choice. There are enough differences across fields such that risk-averse individuals could be made worse off from variability in earnings when making 2-year degree decisions. However, the potential utility loss from ignoring such factors likely are modest and are considerably smaller than in the case of 4-year students.

d. Correlation Between Average Earnings and CV Effects

To characterize the private welfare consequences of major choice, it is important to understand how the effect on average earnings correlates with the effect on earnings variability (i.e., the coefficient of variation). If these move in different directions, then it means that high-return majors are even more attractive than is indicated by examining mean returns alone, because the high-return majors also come with lower within-worker variability. Conversely, if the mean and CV effects move in the same direction, it indicates a tradeoff between the earnings level and variability.

Figure 7 shows these correlations for four-year students (panel a) and two-year students (panel b).[24] In both sectors, the mean earnings effect is negatively correlated with the level effect, with the strength of this negative correlation higher in the four-year sector at -0.56 than in the two-year sector at -0.21. These negative correlations indicate that the mean and CV effects reinforce one another: majors with the highest relative earnings also exhibit lower earnings variability. These majors therefore are even more desirable than the mean estimates suggest. In the four-year sector, this pattern is easier to interpret because the relative earnings effects are all positive and the CV estimates are negative (which indicates less variability). The high return majors exhibit lower variability, both of which make these majors more attractive to students.

In the two-year sector, some earnings estimates are negative, as are most of the coefficient of variation effects. Especially for some of the majors with earnings returns above zero, the CV effects are the most negative. Hence, the majors in the upper left quadrant of the figure are more desirable than the mean estimates would suggest. These results further highlight the importance of moving beyond an examination of the mean in characterizing the return to college major.

e. Aggregation Effects

In all of the prior analyses, we aggregate CIP-4 major categories into 11-12 groups for empirical tractability and to align our approach with the rest of the literature. Such aggregation is ubiquitous in studies on the returns to college major. In Figure 8, we present evidence of variation in returns across disaggregated majors within major groups. To do so, we estimate equation (3) separately for each major group and include indicators for each CIP-4 major included in the aggregate category. We then add back in the average difference between each major and liberal arts to facilitate comparisons with our prior estimates. Thua, the liberal arts estimates are distributed around zero by design. In panel (a) (four-year) and panel (b) (two-year), the aggregate major groups have explanatory power insofar as the distribution of CIP-4 effects do not fully overlap across groups. However, there also is substantial variation within each major category. The extent of this variation varies across groups, with engineering and architecture, vocational, and IT exhibiting large differences across specific majors in the four-year sector and vocational, biology and health, and agriculture exhibiting such variation in the two-year sector.

[24] The mean estimates come from column (9) of Appendix Tables A-5 and A-6 (i.e., the estimates for years 16-20), and the CV estimates come from column (2) of Tables 2 and 3.

These results strongly suggest that major aggregation decisions are not innocuous and that some of the variation in findings across prior studies could reflect different ways of grouping majors together. They also point to the value of future research on how best to aggregate majors such that they are measuring similar skills or they experience similar returns (e.g. Hemelt et al, 2021).

Figure 9 presents estimates of program-specific effects that are estimated using a version of equation (3) where we interact each major group with indicators for each postsecondary institution. These results show that there is substantial variation in returns across programs. Indeed, the program-specific variation appears larger than the variation across major groupings, as the distributions of these estimates overlap substantially across the major categories. In the four-year sector, most of the program-specific returns are positive outside of agriculture and communications. But in no case is the return to every program positive. The program-specific returns in the two-year sector are even more dispersed, with a large mix of positive and negative estimates for each major group.

Unlike the findings in Norway (Kirkeboen, Leuven, and Mogstad 2016), these results point to the importance of major-institution interactions in the US context. Providing students with evidence on the average return to a major across institutions could be highly misleading, as there are large program-specific effects. These estimates raise the important question of why these estimates vary so much across institution, which is a ripe area for future research.

VI. Conclusion

There is a growing body of research examining the returns to college major. This research focuses almost exclusively on the mean returns and pays little attention to how returns vary as workers gain experience in the labor market or variability around this mean. In this paper, we fill several gaps in our knowledge of how major choice in college affects subsequent labor market outcomes. We use administrative data from Texas that allows us to link all public K-12 students in the state with all public higher education students and quarterly earnings records for all Texas workers. 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 also explore the implication of major aggregation that is highly prevalent in the literature.

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

Second, we move beyond the mean to estimate two forms of earnings variation. We first estimate quantile treatment effects of college major on earnings. These estimates show how much variation there is across workers in the return to majors by showing how majors differentially affect parts of the earnings distribution. Our results indicate 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, 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 over time. Our results show that most majors reduce the variability of earnings relative to liberal arts – up to 20% – however the estimates in the two-year sector are much smaller than those in the four-year sector and suggest little overall relevance of major choice on earnings variability in that sector.

Third, we show how average earnings returns and earnings variability are correlated. Majors with higher relative returns experience larger relative reductions in the coefficient of variation. This finding suggests that higher-returns majors are even more attractive than previously thought as they also come with more stable earnings. Fourth, we show evidence of substantial variation in returns across specific majors within each aggregated major group and across institutions for each aggregated major. These results highlight the importance of carefully considering how researchers aggregate majors and institution-specific program effects.

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), 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. (forthcoming) show that students' major choices are responsive to information on mean returns and other potential non-earnings returns. An open 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.

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Table 1: Summary Statistics of Analysis Variables

	4-year Students		2-year Students	
Variable	Mean	SD	Mean	SD
Math Exam Score	0.558	0.696	0.054	0.870
Reading Exam Score	0.515	0.591	0.091	0.827
Top Ten Percent Math	0.260	0.439	0.153	0.360
70th-90th Percentile Math	0.295	0.456	0.183	0.387
Top Ten Percent Reading	0.276	0.444	0.177	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	0.500
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	0.380	0.380	0.485
Economically Disadvantaged	0.164	0.370	0.277	0.447
Earnings 5-10 Years Post-HS	6,788	6,149	5,592	5,258
Earnings 10-15 Years Post-HS	12,338	12,665	8,726	8,386
Earnings 15-20 Years Post-HS	16,793	16,555	11,627	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	0.027		0.126	
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 - 4-year Students

	Dependent Variable: Absolute Variation Relative to:					
	Linear Prediction		4Q Moving Average		8Q Moving Average	
Field of Study	(1)	(2)	(3)	(4)	(5)	(6)
Agriculture	-0.119	-0.080	-0.067	-0.038	-0.082	-0.046
	(0.004)	(0.005)	(0.004)	(0.004)	(0.008)	(0.008)
Communications	-0.098	-0.094	-0.051	-0.056	-0.072	-0.090
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)
IT	-0.102	-0.128	-0.094	-0.120	-0.134	-0.182
	(0.041)	(0.042)	(0.006)	(0.006)	(0.011)	(0.012)
Vocational	-0.129	-0.129	-0.080	-0.082	-0.118	-0.120
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
Engineering + Architecture	-0.139	-0.147	-0.080	-0.097	-0.098	-0.141
	(0.003)	(0.004)	(0.003)	(0.003)	(0.006)	(0.006)
Biology + Health	-0.060	-0.047	-0.035	-0.031	-0.035	-0.035
	(0.006)	(0.006)	(0.003)	(0.003)	(0.005)	(0.005)
Physical Sciences + Math	-0.093	-0.084	-0.052	-0.055	-0.053	-0.069
	(0.005)	(0.006)	(0.005)	(0.005)	(0.009)	(0.009)
Social Sciences	-0.050	-0.038	-0.021	-0.017	-0.021	-0.021
	(0.017)	(0.016)	(0.002)	(0.002)	(0.005)	(0.005)
Business + Economics	-0.148	-0.150	-0.100	-0.106	-0.166	-0.182
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)
Undeclared	-0.059	-0.100	-0.013	-0.041	-0.098	-0.134
	(0.006)	(0.006)	(0.005)	(0.005)	(0.010)	(0.009)
Constant	0.677	0.671	0.551	0.548	0.956	0.961
	(0.002)	(0.014)	(0.002)	(0.014)	(0.004)	(0.029)
Controls		x		x		x
High School-Cohort & College-Cohort FE		x		x		x
Observations	486,950	486,040	487,816	486,906	487,809	486,897
Dep. Var. Mean	0.607	0.607	0.510	0.510	0.894	0.894

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 coefficient of variation, the calculation of which varies across columns based how wages are predicted. 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 high schools level are in parentheses.

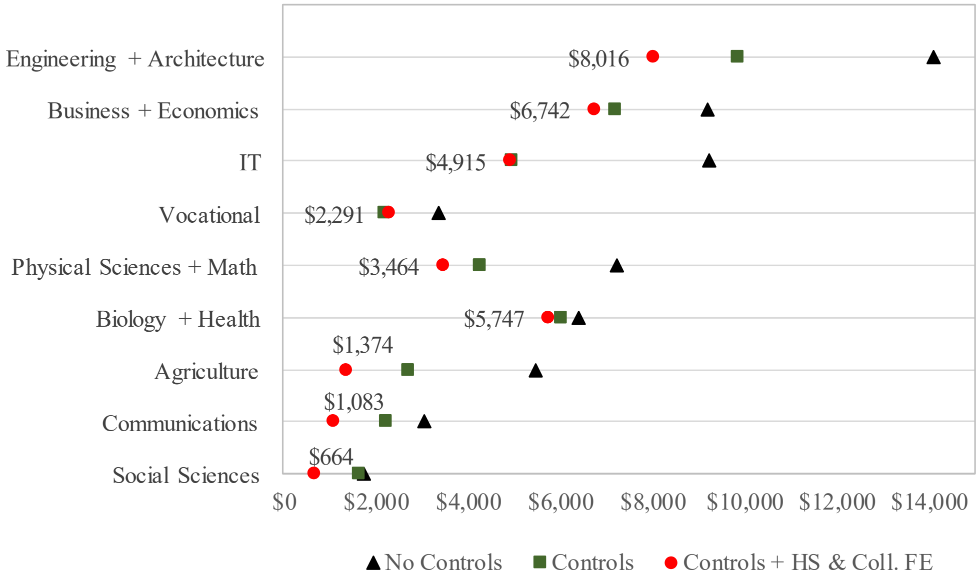
Table 3: The Effect of College Major Choice on Earnings Variability - 2-year Students

	Dependent Variable: Absolute Variation Relative to:					
	Linear Prediction		4Q Moving Average		8Q Moving Average	
Field of Study	(1)	(2)	(3)	(4)	(5)	(6)
Agriculture	-0.062	-0.036	-0.057	-0.020	-0.088	-0.036
	(0.009)	(0.012)	(0.010)	(0.009)	(0.018)	(0.018)
Communications	-0.036	-0.042	-0.016	-0.018	-0.043	-0.047
	(0.008)	(0.010)	(0.009)	(0.009)	(0.016)	(0.015)
IT	-0.069	-0.057	-0.064	-0.047	-0.108	-0.075
	(0.009)	(0.010)	(0.004)	(0.004)	(0.007)	(0.007)
Vocational	-0.092	-0.072	-0.084	-0.064	-0.159	-0.114
	(0.009)	(0.011)	(0.003)	(0.002)	(0.004)	(0.004)
Engineering + Architecture	-0.031	-0.015	-0.014	-0.001	-0.026	-0.009
	(0.008)	(0.008)	(0.008)	(0.008)	(0.016)	(0.016)
Biology + Health	-0.057	-0.065	-0.049	-0.050	-0.095	-0.091
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)
Physical Sciences + Math	0.000	0.003	-0.000	0.004	0.021	0.016
	(0.008)	(0.008)	(0.008)	(0.008)	(0.016)	(0.016)
Social Sciences	-0.013	-0.022	-0.007	-0.011	-0.019	-0.017
	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)
Business + Economics	-0.066	-0.064	-0.053	-0.047	-0.104	-0.088
	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)
Education	-0.041	-0.050	-0.038	-0.039	-0.071	-0.066
	(0.004)	(0.005)	(0.004)	(0.004)	(0.007)	(0.006)
Undeclared	-0.100	-0.097	-0.085	-0.079	-0.130	-0.117
	(0.008)	(0.008)	(0.003)	(0.002)	(0.005)	(0.005)
Constant	0.674	0.734	0.579	0.630	0.905	1.001
	(0.002)	(0.013)	(0.002)	(0.013)	(0.003)	(0.027)
Controls		x		x		x
High School-Cohort & College-Cohort FE		x		x		x
Observations	507,508	506,387	507,846	506,724	507,758	506,634
Dep. Var. Mean	0.634	0.634	0.546	0.546	0.843	0.843

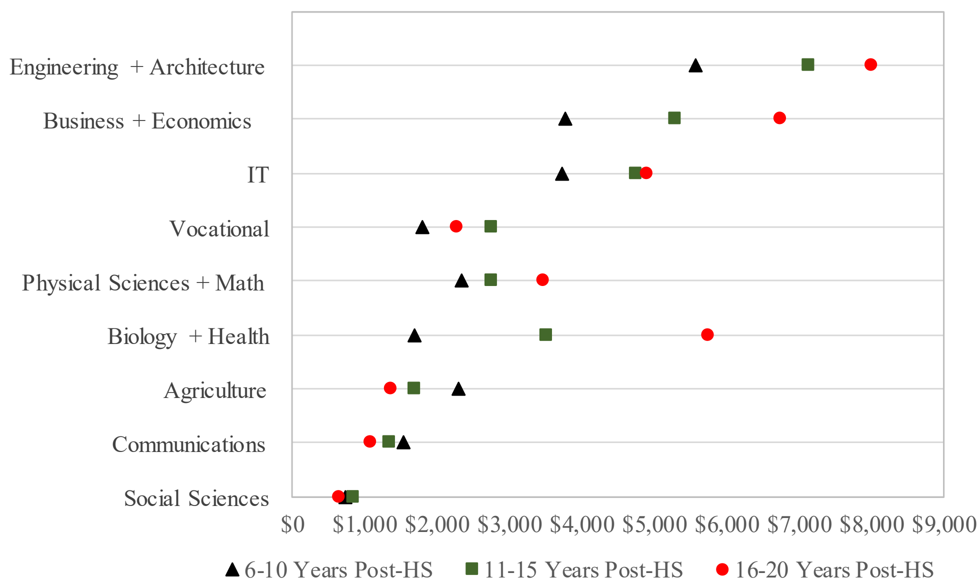
Notes: Authors' estimation as described in the text using linked administrative K-12, higher education, and quarterly earnings data from Texas. Each column is a separate regression. The dependent variable is the coefficient of variation, the calculation of which varies across columns based how wages are predicted. 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 high schools 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



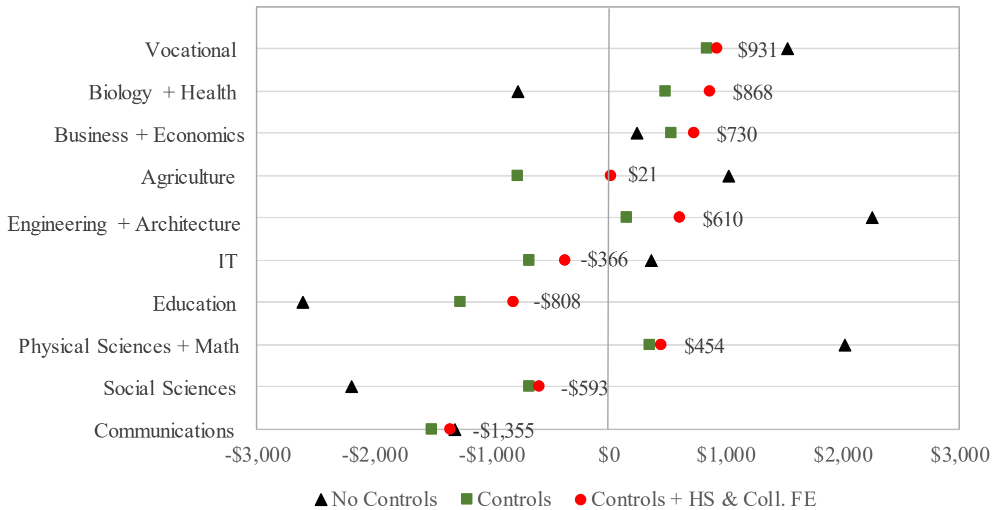
(b) Return to College Major by Potential Experience



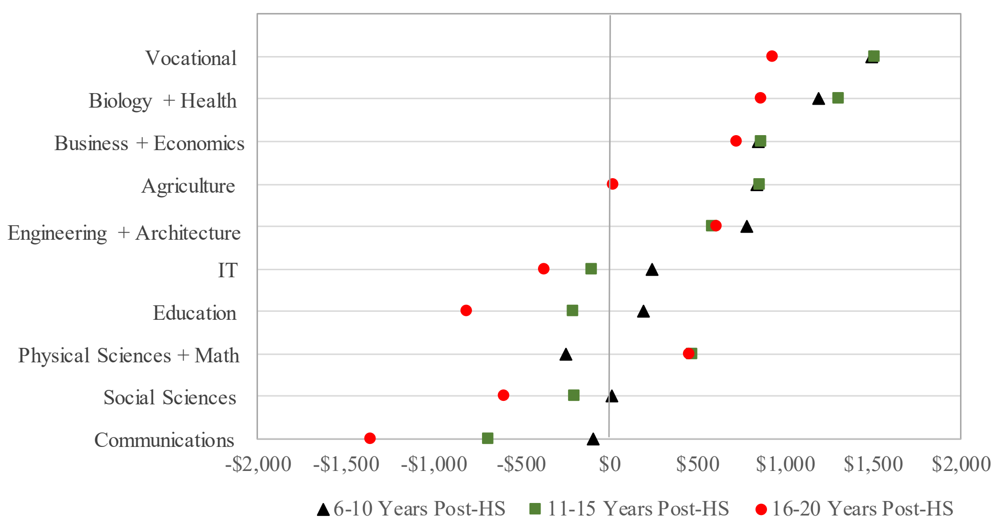
Notes: All estimates are relative to liberal arts majors. "Controls" include measures of high school test scores, and student demographic characteristics. All estimates in panel (b) include controls, HS-by-cohort, and post-secondary institution-by-cohort fixed effects. Outcomes are in dollars of quarterly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

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

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

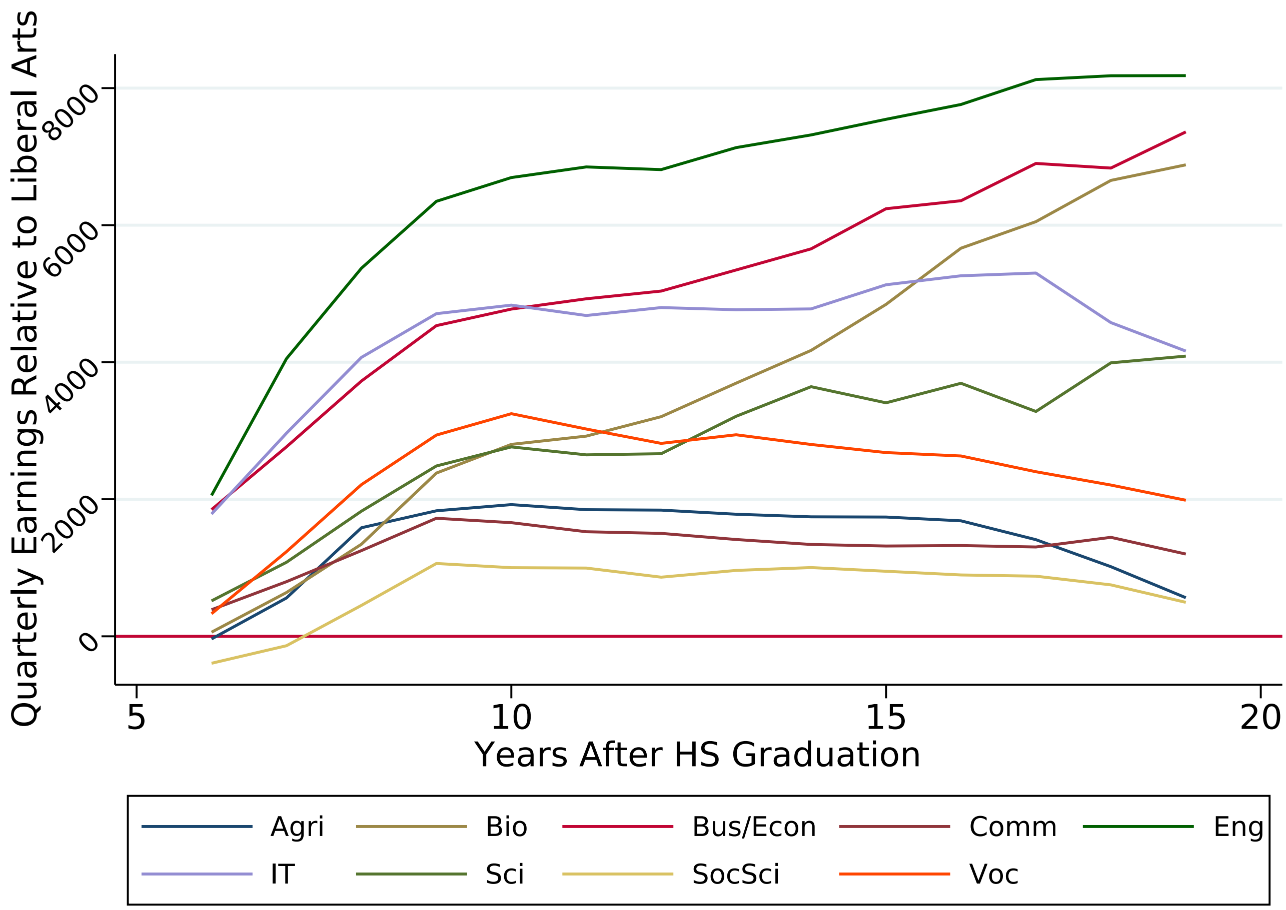


(b) Return to College Major by Potential Experience



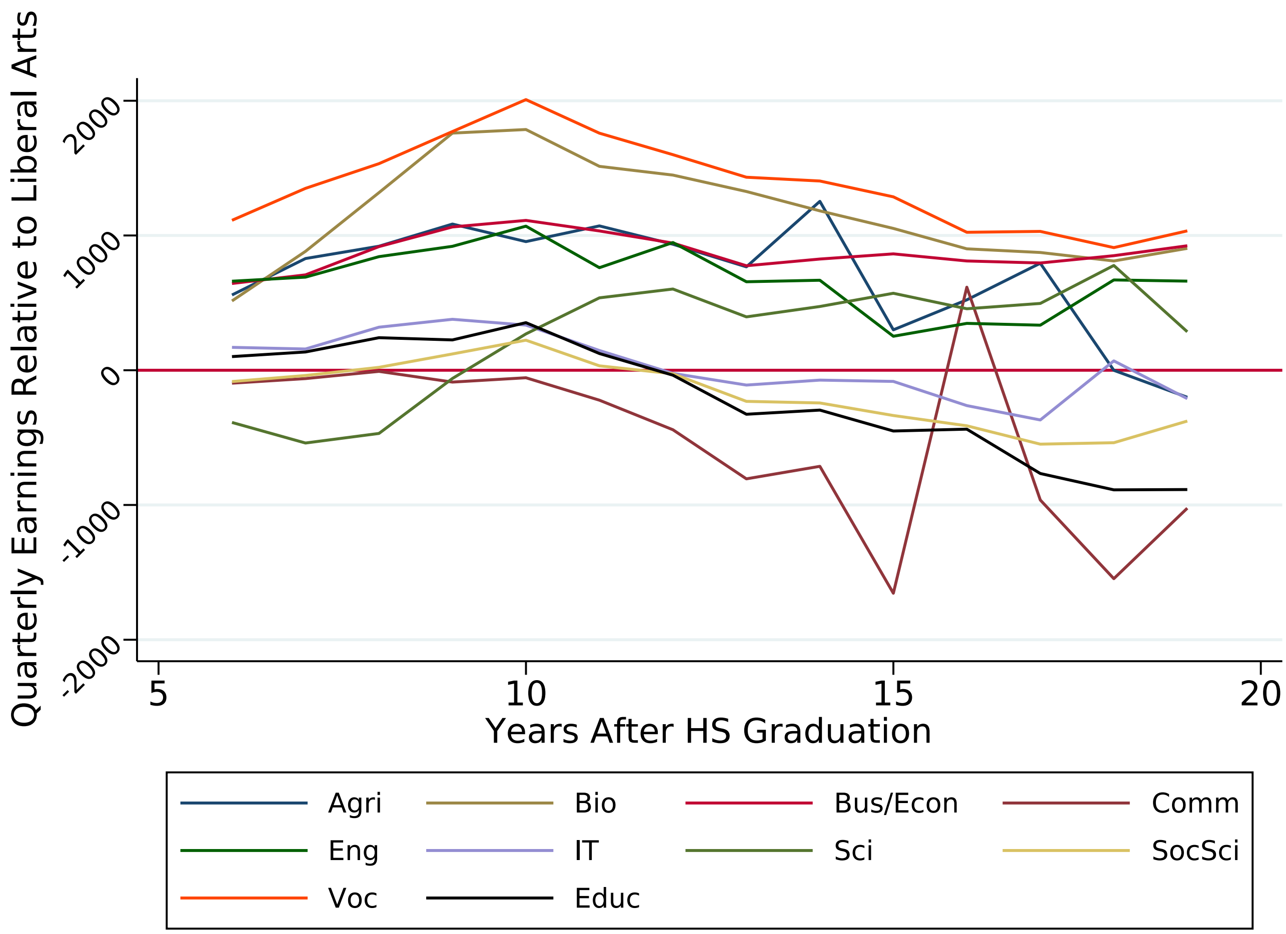
Notes: All estimates are relative to liberal arts majors. "Controls" include measures of high school test scores, and student demographic characteristics. All estimates in panel (b) include controls, HS-by-cohort, and post-secondary institution-by-cohort fixed effects. Outcomes are in dollars of quarterly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

Figure 3: Earnings Effects of Largest Majors by Potential Experience - 4-year Students



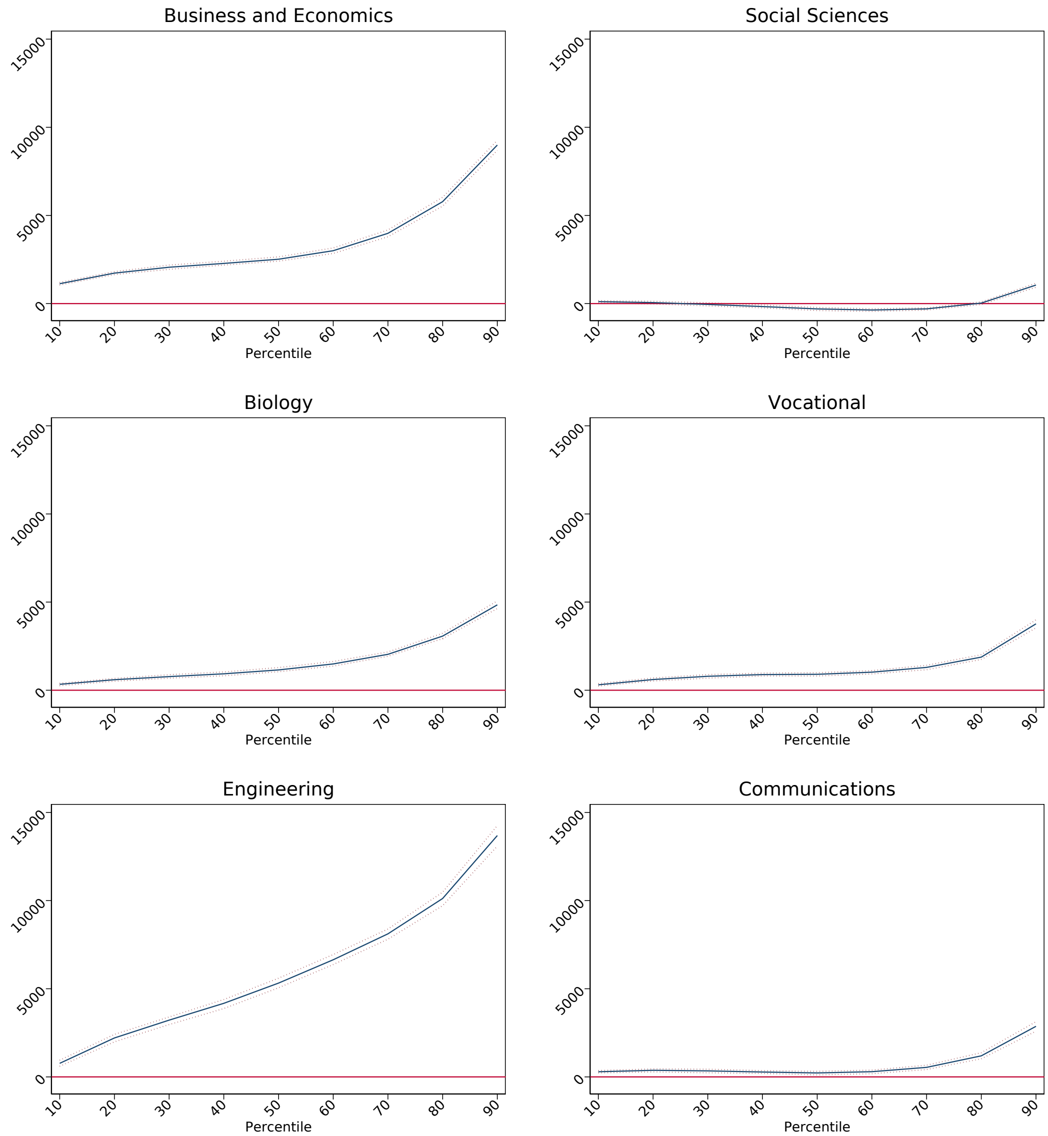
Notes: All estimates are relative to liberal arts majors and include controls for high school test scores, student demographics, cohort fixed effects, HS-by-cohort fixed effects, and college-by-cohort fixed effects. Outcomes are 4-quarter moving average quarterly earnings ($2016). Each curve comes from estimates of the returns to each major for each year of potential experience, measured by years since high school graduation.

Figure 4: Earnings Effects of Largest Majors by Potential Experience - 2-year Students



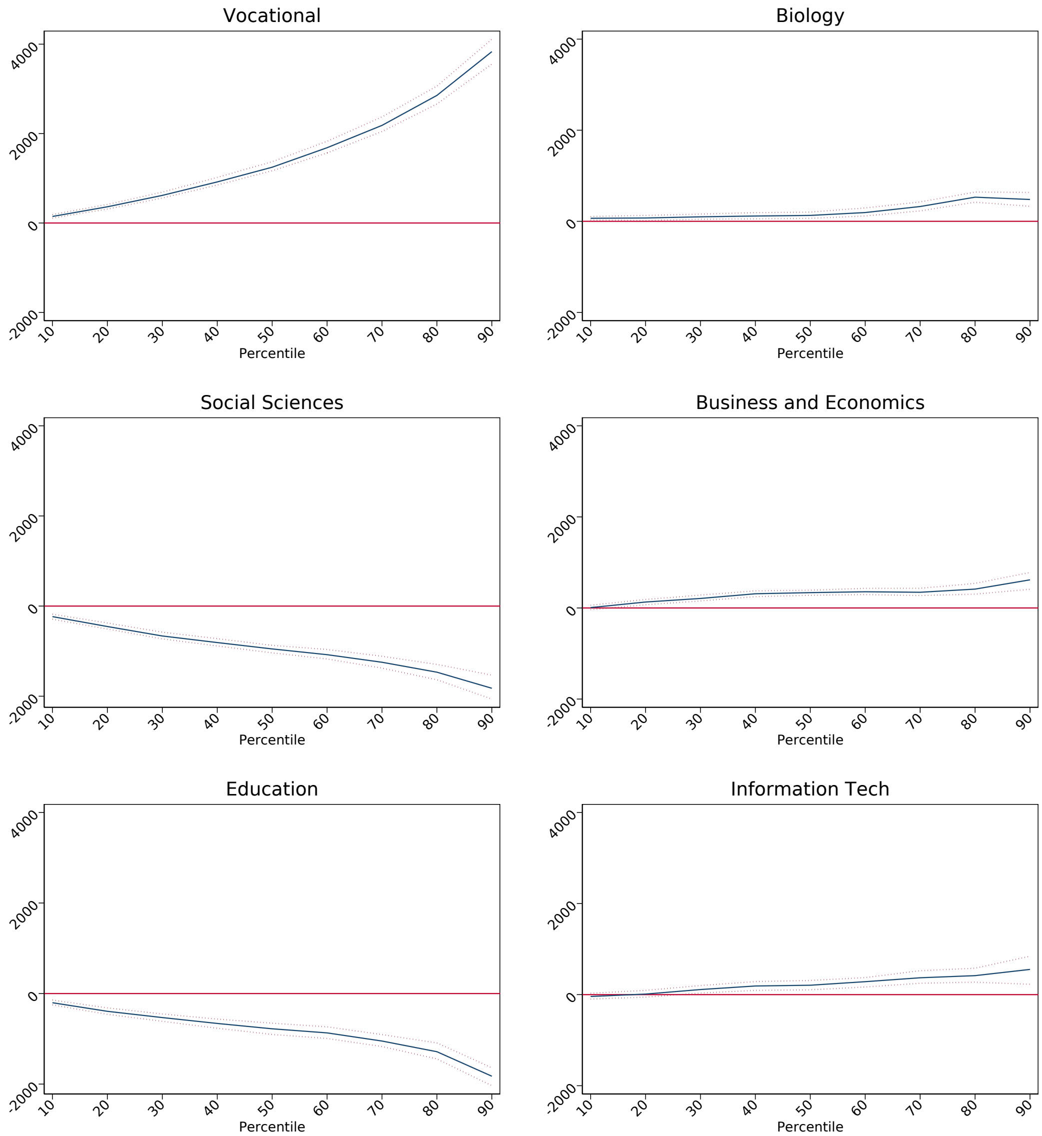
Notes: All estimates are relative to liberal arts majors and include controls for high school test scores, student demographics, cohort fixed effects, HS-by-cohort fixed effects, and college-by-cohort fixed effects. Outcomes are 4-quarter moving average quarterly earnings ($2016). Each curve comes from estimates of the returns to each major for each year of potential experience, measured by years since high school graduation.

Figure 5: Quantile Treatment Effects of Major on Average Quarterly Earnings - 4-year Students



Notes: Figure shows results for six largest broad fields in size order. Additional fields provided in Appendix Figure A-4. All estimates are relative to liberal arts majors and 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 dots show the 95% confidence interval, calculated using a black bootstrap at the postsecondary institution level.

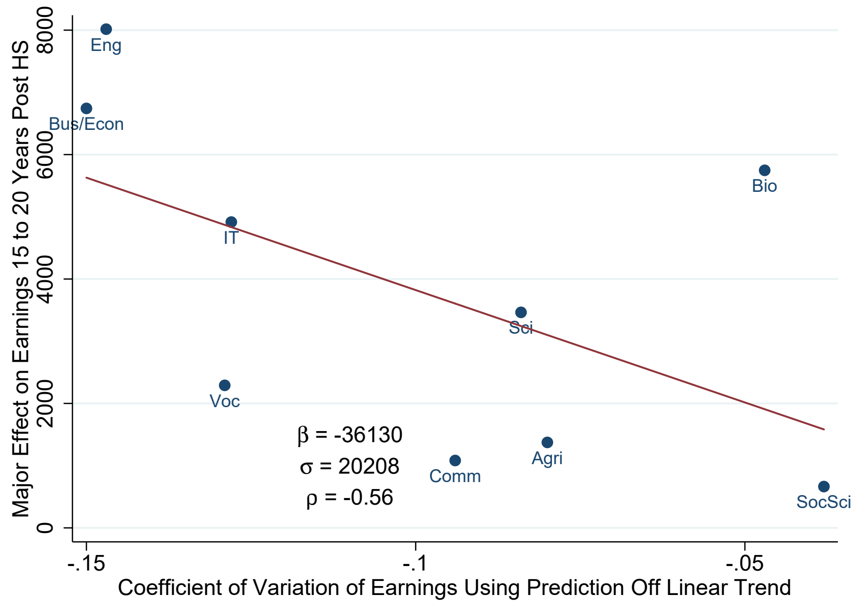
Figure 6: Quantile Treatment Effects of Major on Average Quarterly Earnings - 2-year Students



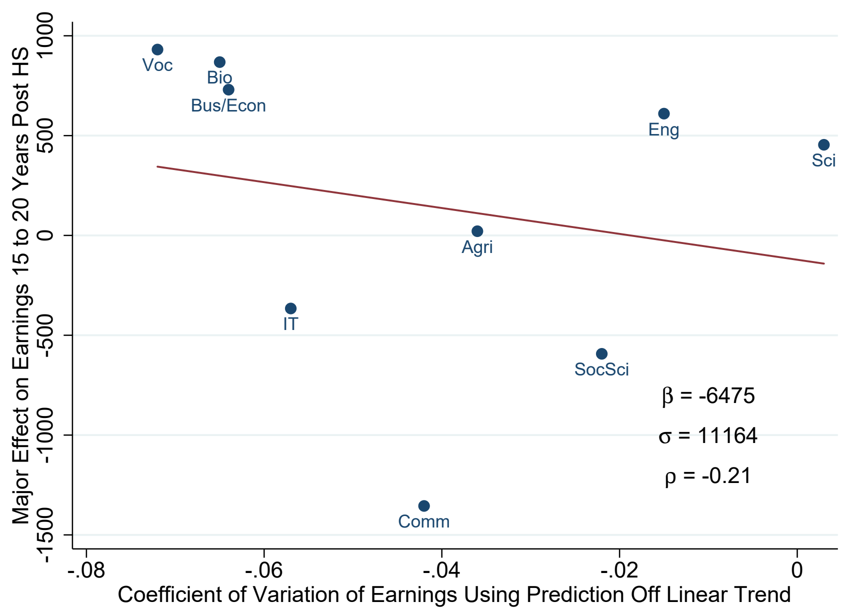
Notes: Figure shows results for six largest broad fields in size order. Additional fields provided in Appendix Figure A-5. All estimates are relative to liberal arts majors and include controls for high school test scores, student demographics, HS-by-cohort fixed effects, and college-by-cohort fixed 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 dots show the 95% confidence interval, calculated using a black bootstrap at the postsecondary institution level.

Figure 7: The Correlation Between Mean Earnings Effects and Effects on the Coefficient of Variation

(a) 4-year Students



(b) 2-year Students

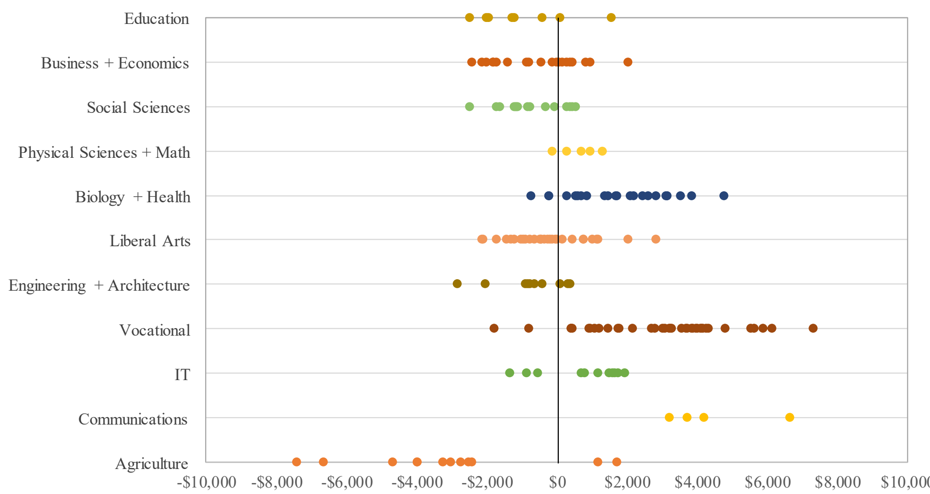


Notes: All estimates are relative to liberal arts majors. "Controls" include measures of high school test scores, student demographic characteristics, and HS cohort fixed effects. Outcomes are in dollars of quarterly earnings. β and σ are the coefficient and standard error from a regression of earnings on the coefficient of variation. ρ is the Pearson correlation coefficient for these two measures.

Figure 8: Variation in Mean Earnings Effects Across CIP-4 Major Categories

(a) 4-year Students

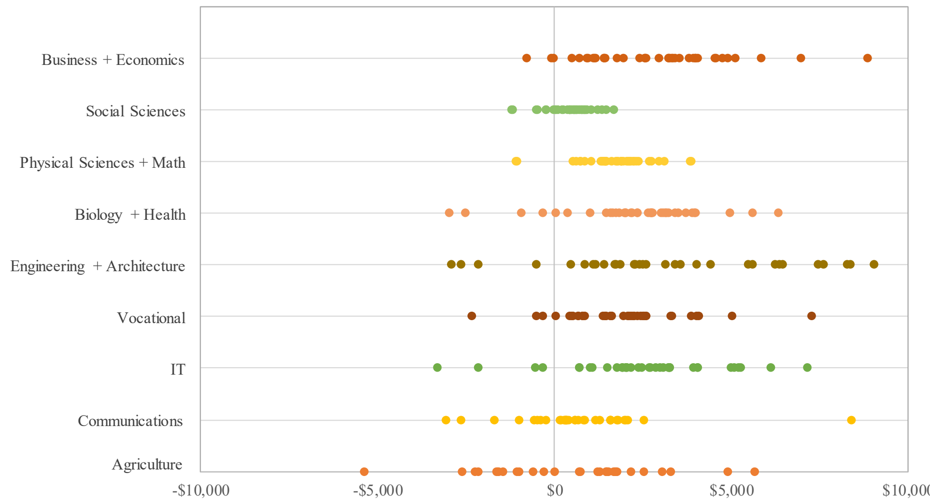
(b) 2-year Students



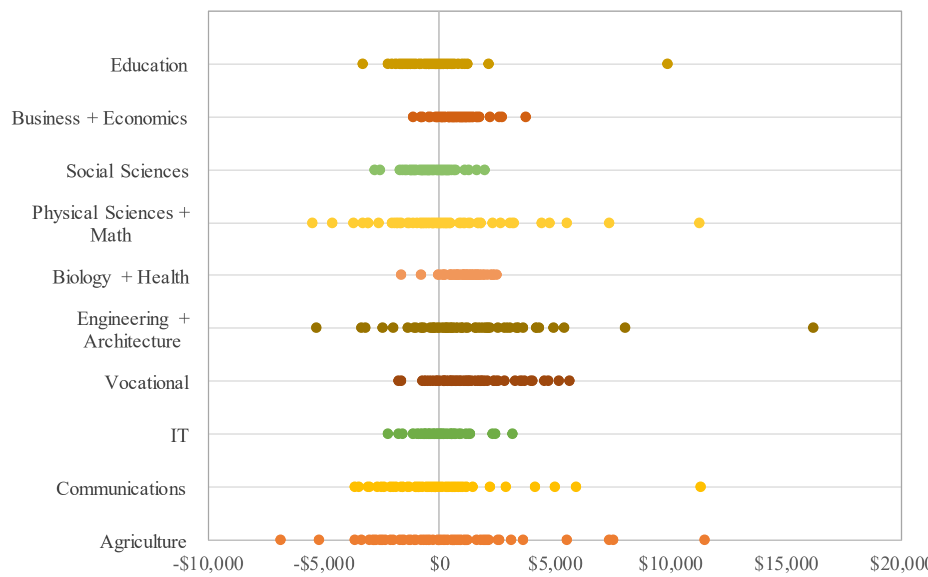
Notes: All estimates are relative to mean differences between each major category and liberal arts. "Controls" include measures of high school test scores, student demographic characteristics, and HS cohort fixed effects. Outcomes are in dollars of quarterly earnings.

Figure 9: Variation in Mean Earnings Effects Across Institutions

(a) 4-year Students



(b) 2-year Students



Notes: All estimates are relative to mean differences between each major category and liberal arts. "Controls" include measures of high school test scores, student demographic characteristics, and HS cohort fixed effects. Outcomes are in dollars of quarterly earnings.

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

	Four-year			Two-year		
	Quarters Non-Zero Earnings	Quarters Zero Earnings	I(Leave Earnings Sample)	Quarters Non-Zero Earnings	Quarters Zero Earnings	I(Leave Earnings Sample)
Field of Study	(1)	(2)	(3)	(4)	(5)	(6)
Agriculture	2.39	-0.65	-0.00	0.22	0.60	0.00
	(0.145)	(0.088)	(0.004)	(0.325)	(0.235)	(0.010)
Communications	2.50	-0.80	-0.03	0.89	-0.25	-0.01
	(0.105)	(0.076)	(0.003)	(0.277)	(0.197)	(0.009)
IT	4.28	-2.00	-0.09	1.61	-0.73	-0.04
	(0.196)	(0.124)	(0.006)	(0.134)	(0.090)	(0.004)
Vocational	3.97	-1.51	-0.05	2.52	-0.83	-0.05
	(0.097)	(0.053)	(0.003)	(0.083)	(0.057)	(0.003)
Engineering + Architecture	3.79	-1.64	-0.06	0.20	0.20	-0.00
	(0.118)	(0.072)	(0.004)	(0.274)	(0.172)	(0.008)
Biology + Health	2.02	0.20	0.02	2.52	-1.04	-0.04
	(0.094)	(0.063)	(0.003)	(0.071)	(0.050)	(0.002)
Physical Sciences + Math	2.21	-0.61	-0.03	-0.06	-0.00	0.00
	(0.156)	(0.104)	(0.005)	(0.289)	(0.186)	(0.008)
Social Sciences	1.50	-0.15	0.02	0.51	0.11	0.00
	(0.087)	(0.051)	(0.002)	(0.119)	(0.087)	(0.004)
Business + Economics	4.92	-2.00	-0.09	1.98	-0.77	-0.04
	(0.070)	(0.042)	(0.002)	(0.083)	(0.054)	(0.003)
Education				1.38	-0.16	-0.01
				(0.130)	(0.087)	(0.004)
Constant	29.78	7.51	0.67	28.15	9.10	0.73
	(0.563)	(0.311)	(0.015)	(0.442)	(0.282)	(0.012)
Controls	x	x	x	x	x	x
High School & College FE	x	x	x	x	x	x
Observations	491,343	491,343	491,343	508,519	508,519	508,519

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 high school level are in parentheses.

Table A-3: Means of Analysis Variables by Major

Variable	Liberal Arts	Agri-culture	Comm-unications	IT	Voc-ational	Eng. & Arch.	Bio & Health	Science & Math	Social Science	Bus. & Econ.	Educ-ation	Undec-lared
4-year Students												
Math Exam Score	0.475	0.607	0.532	0.865	0.393	0.967	0.655	0.965	0.513	0.680		0.346
Reading Exam Score	0.521	0.544	0.610	0.615	0.346	0.676	0.582	0.672	0.571	0.538		0.325
Top Ten Percent Math	0.212	0.248	0.231	0.445	0.182	0.516	0.309	0.507	0.227	0.301		0.205
70th-90th Percentile Math	0.287	0.326	0.299	0.317	0.274	0.300	0.308	0.311	0.298	0.324		0.240
Top Ten Percent Reading	0.282	0.276	0.316	0.346	0.192	0.378	0.314	0.363	0.299	0.277		0.217
70th-90th Percentile Reading	0.293	0.308	0.320	0.314	0.258	0.318	0.305	0.325	0.308	0.301		0.244
Male	0.306	0.609	0.364	0.850	0.618	0.754	0.285	0.549	0.292	0.530		0.537
White	0.668	0.905	0.663	0.632	0.584	0.655	0.539	0.673	0.629	0.648		0.452
Hispanic	0.225	0.064	0.184	0.164	0.240	0.197	0.242	0.207	0.212	0.176		0.282
Black	0.079	0.025	0.111	0.085	0.154	0.054	0.117	0.052	0.115	0.092		0.202
Asian	0.026	0.005	0.040	0.117	0.020	0.092	0.100	0.065	0.043	0.082		0.062
At Risk	0.179	0.128	0.143	0.137	0.225	0.103	0.150	0.105	0.164	0.142		0.277
Economically Disadvantaged	0.162	0.055	0.107	0.152	0.202	0.138	0.193	0.156	0.152	0.133		0.232
Earnings 6-10 Years Post-HS	6,170	7,394	6,636	8,874	6,868	10,653	6,778	7,537	5,835	8,844		6,308
Earnings 11-15 Years Post-HS	10,268	13,393	11,684	16,094	12,434	19,700	13,257	14,249	10,815	15,773		10,544
Earnings 16-20 Years Post-HS	13,019	18,036	15,658	21,987	15,895	26,690	18,931	20,049	14,326	21,694		14,546
2-year Students												
Math Exam Score	0.089	0.012	0.009	0.098	-0.125	0.359	0.005	0.535	-0.099	0.071	-0.110	0.130
Reading Exam Score	0.152	0.009	0.257	0.031	-0.172	0.157	0.090	0.350	0.082	0.049	-0.014	0.164
Top Ten Percent Math	0.154	0.150	0.134	0.177	0.163	0.219	0.125	0.276	0.129	0.141	0.117	0.181
70th-90th Percentile Math	0.193	0.174	0.182	0.200	0.141	0.255	0.173	0.295	0.154	0.189	0.144	0.196
Top Ten Percent Reading	0.184	0.172	0.198	0.175	0.172	0.182	0.157	0.220	0.176	0.153	0.145	0.207
70th-90th Percentile Reading	0.205	0.173	0.234	0.181	0.132	0.215	0.189	0.263	0.188	0.182	0.172	0.205
Male	0.458	0.811	0.519	0.760	0.766	0.874	0.242	0.569	0.236	0.466	0.306	0.490
White	0.552	0.877	0.504	0.485	0.480	0.452	0.500	0.526	0.462	0.477	0.463	0.567
Hispanic	0.287	0.092	0.363	0.331	0.395	0.440	0.363	0.372	0.380	0.354	0.423	0.272
Black	0.132	0.029	0.122	0.155	0.112	0.083	0.114	0.071	0.145	0.146	0.106	0.129
Asian	0.026	0.001	0.008	0.026	0.011	0.024	0.021	0.028	0.010	0.020	0.006	0.029
At Risk	0.358	0.366	0.373	0.405	0.478	0.351	0.387	0.268	0.415	0.379	0.418	0.349
Economically Disadvantaged	0.243	0.119	0.262	0.305	0.345	0.334	0.313	0.270	0.328	0.293	0.368	0.212
Earnings 6-10 Years Post-HS	5,270	6,612	4,721	5,550	6,729	6,245	5,669	5,081	4,381	5,728	4,592	6,417
Earnings 11-15 Years Post-HS	8,528	9,987	7,422	8,652	10,082	10,042	8,476	9,651	6,815	8,802	6,845	9,735
Earnings 16-20 Years Post-HS	11,436	12,462	10,163	11,723	12,775	13,707	10,679	13,455	9,229	11,672	8,887	13,005

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	2176.93	935.839	24.304	7.283	1454.09	684.93	3.578	0.586
	(73.36)	(82.697)	(1.363)	(1.420)	(219.65)	(215.27)	(3.672)	(3.709)
Communications	1579.41	1,139.858	6.437	-1.556	(362.55)	(97.46)	-6.558	-8.303
	(46.87)	(48.221)	(0.858)	(0.923)	(93.66)	(97.07)	(2.135)	(2.147)
IT	3271.61	3,086.113	50.975	21.735	565.15	275.28	-0.376	-5.997
	(109.404)	(112.774)	(2.318)	(2.126)	(63.73)	(62.73)	(1.004)	(1.032)
Vocational	1841.75	1,864.578	13.810	7.237	1934.74	1622.65	-1.094	-3.933
	(45.28)	(45.609)	(0.844)	(0.840)	(79.34)	(54.46)	(0.852)	(0.668)
Engineering + Architecture	5303.85	4,413.512	63.937	30.547	1352.94	976.02	2.580	-8.727
	(115.45)	(103.756)	(1.605)	(1.541)	(141.15)	(133.40)	(3.175)	(3.264)
Biology + Health	1201.30	972.698	38.642	36.090	673.10	1255.48	-7.167	-0.800
	(90.80)	(86.590)	(1.803)	(1.582)	(40.19)	(33.29)	(0.630)	(0.527)
Physical Sciences + Math	1912.41	1,279.066	37.127	17.209	15.59	(123.79)	14.900	5.081
	(215.57)	(218.977)	(3.978)	(3.941)	(118.33)	(121.12)	(2.269)	(2.160)
Social Sciences	726.15	345.101	4.763	1.625	(569.68)	110.33	-11.984	-6.238
	(36.40)	(36.097)	(0.746)	(0.755)	(80.45)	(60.38)	(1.183)	(1.083)
Business + Economics	3822.91	3,493.900	37.127	23.376	753.62	900.04	-2.401	-1.742
	(56.13)	(55.834)	(1.142)	(0.972)	(46.52)	(40.77)	(0.678)	(0.636)
Education					427.93	286.55	-14.062	-8.181
					(75.16)	(70.30)	(1.401)	(1.239)
Undeclared	886.59	1,584.26	9.686	2.323	1414.59	1305.46	1.267	-1.628
	(240.98)	(253.69)	(6.953)	(7.435)	(51.22)	(43.39)	(0.987)	(0.849)
Constant	4990.63	4,706.23	58.683	43.849	5075.57	3518.10	44.880	32.337
	(35.64)	(219.96)	(0.501)	(4.335)	(41.77)	(174.42)	(0.547)	(2.527)
Controls		x		x		x		x
High School-Cohort & College-Cohort FE		x		x		x		x
Observations	492,064	491,154	492,064	491,154	509,381	508,260	509,381	508,260
Dep. Var. Mean	6612	6612	77.47	77.47	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 high school 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		
Field of Study	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Agriculture	2,303	1,897	1,024	4,211	2,797	1,704	5,468	2,714	1,374
	(68)	(67)	(78)	(95)	(96)	(98)	(170)	(171)	(178)
Communications	1,549	1,317	1,029	2,485	2,028	1,360	3,061	2,210	1,083
	(40)	(40)	(40)	(85)	(82)	(80)	(146)	(138)	(132)
IT	3,743	3,407	3,419	6,813	4,667	4,748	9,245	4,951	4,915
	(94)	(97)	(94)	(209)	(198)	(191)	(295)	(264)	(247)
Vocational	1,807	1,995	1,812	3,299	2,901	2,769	3,363	2,204	2,291
	(36)	(36)	(36)	(73)	(73)	(70)	(110)	(99)	(100)
Engineering + Architecture	5,571	5,035	4,462	10,526	8,277	7,128	14,102	9,870	8,016
	(110)	(106)	(92)	(235)	(222)	(201)	(261)	(236)	(208)
Biology + Health	1,690	1,477	1,295	4,079	3,789	3,514	6,387	6,024	5,747
	(45)	(45)	(49)	(69)	(66)	(67)	(156)	(146)	(146)
Physical Sciences + Math	2,343	1,750	1,544	4,876	3,216	2,764	7,217	4,254	3,464
	(71)	(70)	(66)	(129)	(130)	(134)	(249)	(254)	(248)
Social Sciences	732	572	282	1,606	1,490	850	1,753	1,627	664
	(26)	(25)	(27)	(55)	(54)	(57)	(95)	(95)	(97)
Business + Economics	3,778	3,531	3,372	6,624	5,593	5,288	9,186	7,181	6,742
	(49)	(51)	(48)	(112)	(102)	(94)	(185)	(163)	(154)
Undeclared	1,255	1,587	1,997	1,427	1,449	1,689	2,078	1,783	2,042
	(58)	(62)	(62)	(150)	(137)	(154)	(256)	(212)	(235)
Constant	5,088	4,383	4,705	9,164	7,257	7,902	12,536	9,313	10,230
	(29)	(182)	(169)	(52)	(280)	(293)	(76)	(555)	(589)

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 high school 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	1,543	781	844	1,726	359	856	1,019	-778	21
	(125)	(117)	(116)	(198)	(187)	(184)	(252)	(239)	(246)
Communications	-338	-370	-90	-877	-959	-688	-1,315	-1,515	-1,355
	(79)	(81)	(79)	(138)	(141)	(143)	(342)	(350)	(336)
IT	546	167	247	421	-390	-102	359	-675	-366
	(45)	(41)	(41)	(76)	(68)	(64)	(122)	(112)	(103)
Vocational	1,782	1,528	1,496	1,972	1,457	1,510	1,530	837	931
	(73)	(60)	(47)	(117)	(90)	(72)	(153)	(117)	(89)
Engineering + Architecture	1,195	496	783	1,741	232	585	2,248	155	610
	(106)	(98)	(94)	(177)	(162)	(158)	(310)	(291)	(289)
Biology + Health	635	1,049	1,190	200	1,064	1,307	-781	487	868
	(35)	(32)	(28)	(63)	(49)	(43)	(96)	(71)	(63)
Physical Sciences + Math	-33	-479	-244	1,313	305	475	2,019	353	454
	(100)	(96)	(100)	(220)	(203)	(192)	(376)	(337)	(304)
Social Sciences	-645	-144	13	-1,440	-385	-192	-2,192	-682	-593
	(58)	(44)	(38)	(113)	(79)	(62)	(187)	(123)	(90)
Business + Economics	698	761	849	524	673	866	244	532	730
	(38)	(33)	(32)	(64)	(54)	(50)	(101)	(83)	(81)
Education	-467	-48	192	-1,478	-581	-201	-2,610	-1,260	-808
	(51)	(46)	(45)	(72)	(61)	(66)	(134)	(116)	(87)
Undeclared	1,408	1,301	1,321	1,518	1,300	1,399	1,641	1,325	1,316
	(43)	(35)	(32)	(86)	(69)	(62)	(156)	(132)	(129)
Constant	5,117	4,031	3,758	8,405	6,088	5,806	11,584	8,095	7,732
	(35)	(128)	(150)	(63)	(205)	(217)	(95)	(345)	(375)
Controls		x	x		x	x		x	x
High School-Cohort & College-Cohort FE			x			x			x
Observations	508,553	508,553	507,433	466,511	466,511	465,381	277,370	277,370	276,584
Dep. Var. Mean	5592	5592	5592	8726	8726	8726	11628	11628	11628

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 high school level are in parentheses.

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

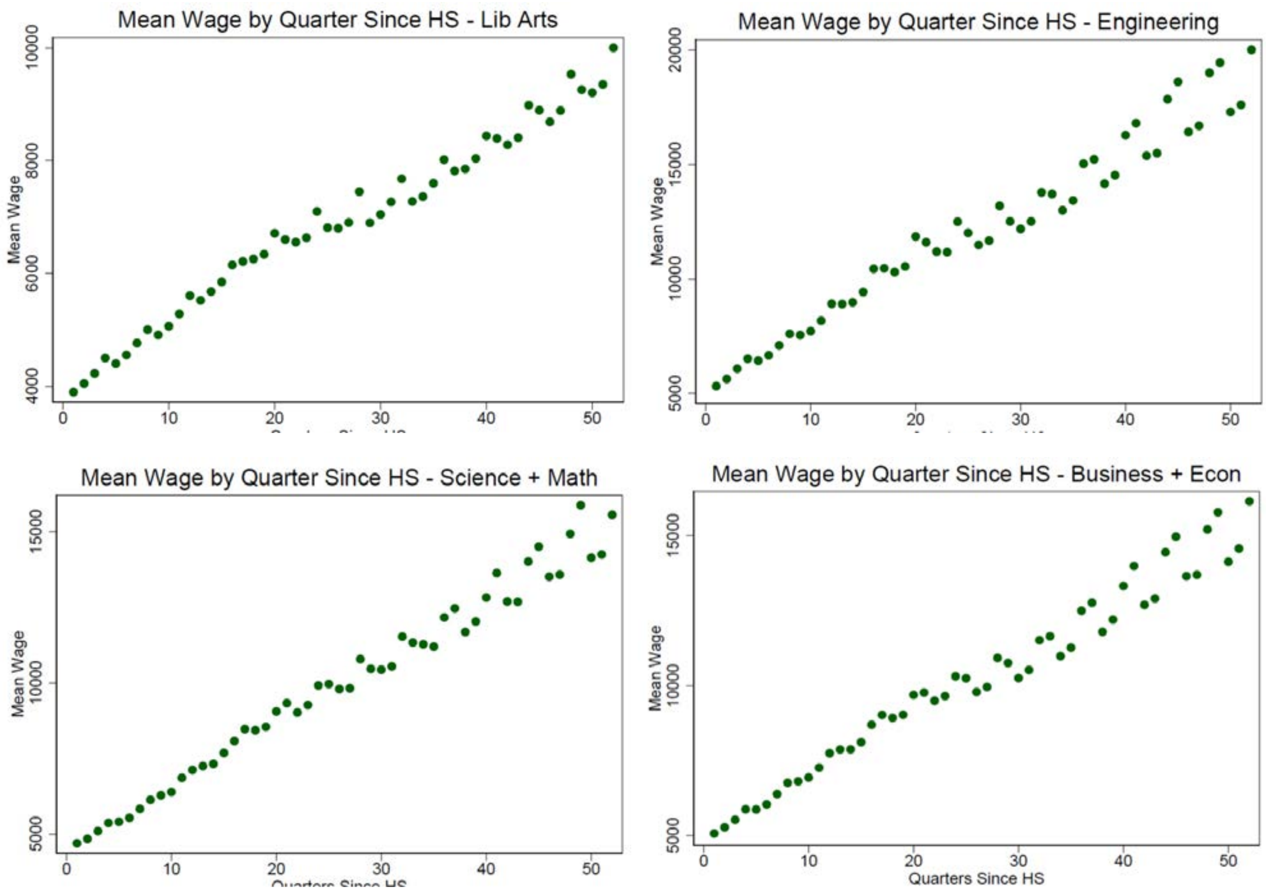
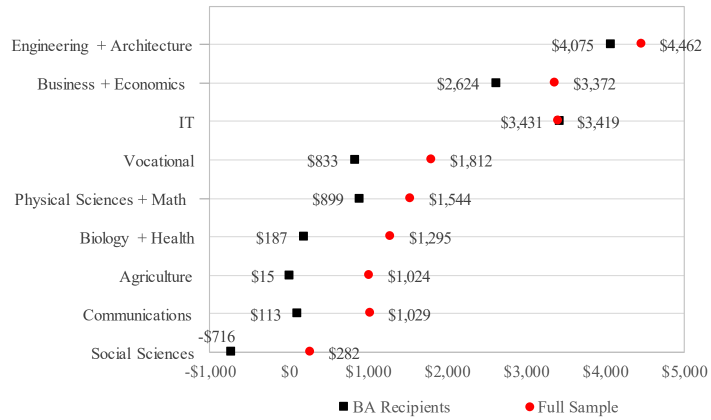
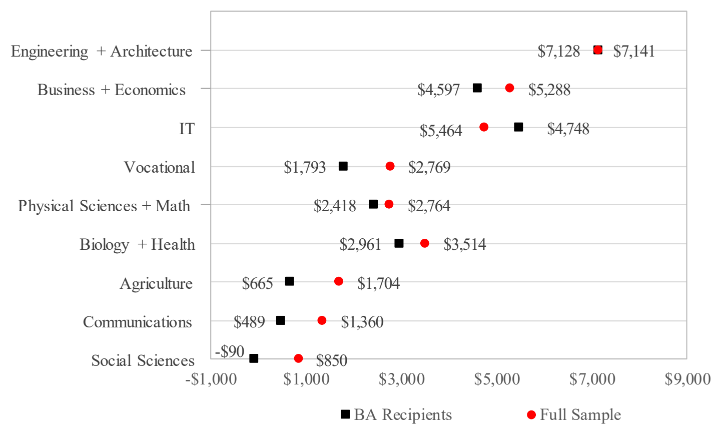


Figure A-2: The Return to College Majors by Years After High School and BA Completion - 4-year Students

(a) 6-10 Years Post-HS



(b) 11-15 Years Post-HS



(c) 16-20 Years Post-HS

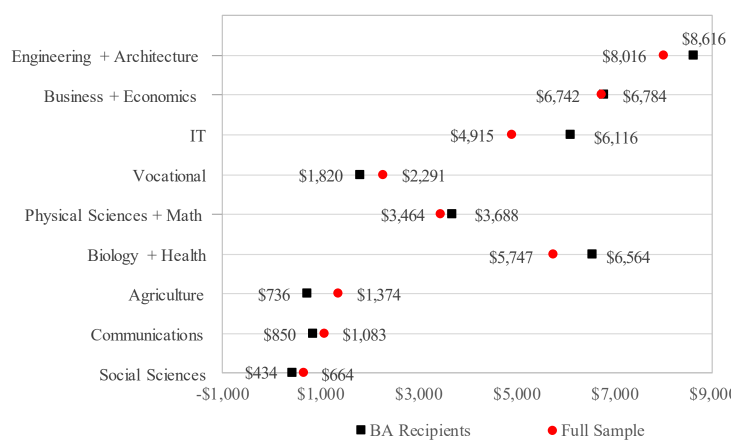
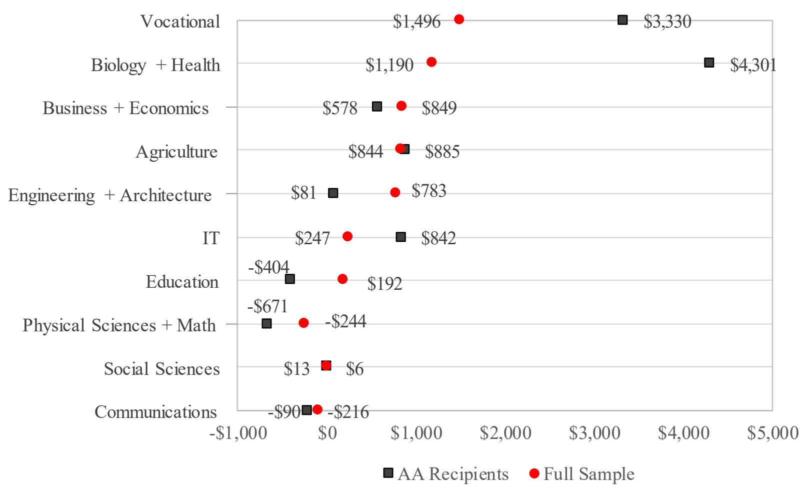
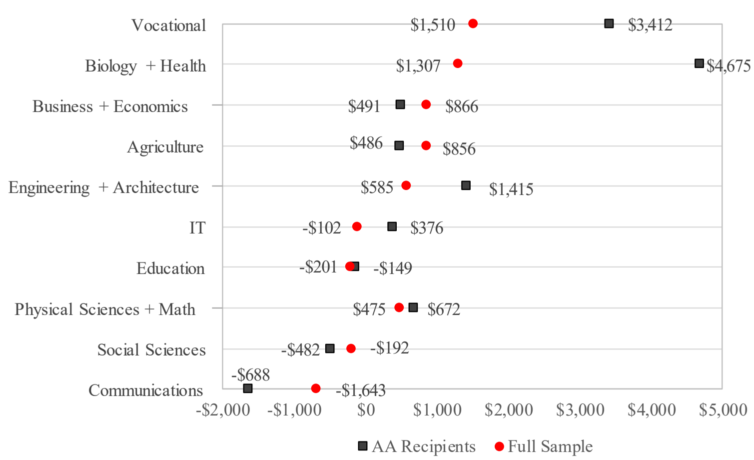


Figure A-3: The Return to College Majors by Years After High School and AA Completion - 2-year Students

(a) 6-10 Years Post-HS



(b) 11-15 Years Post-HS



(c) 16-20 Years Post-HS

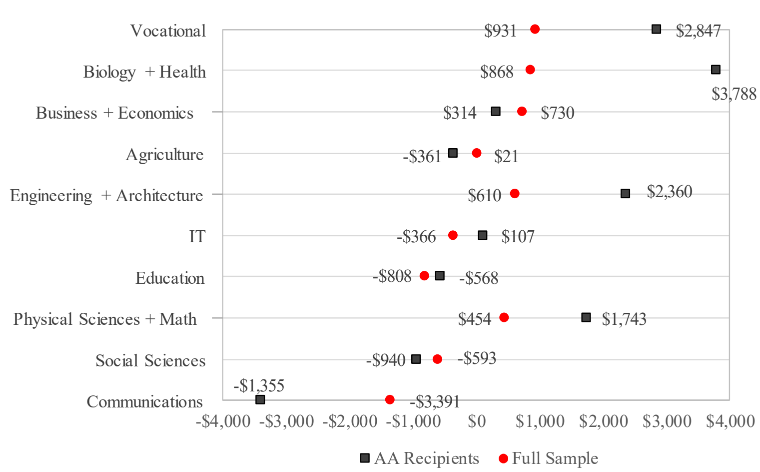
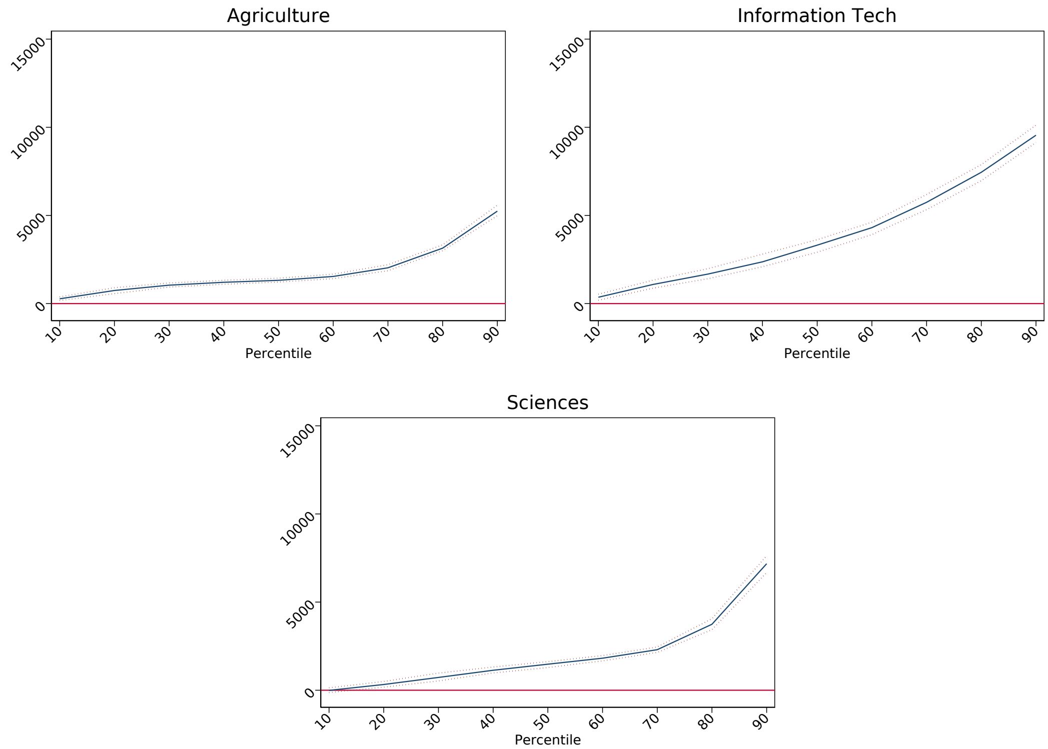
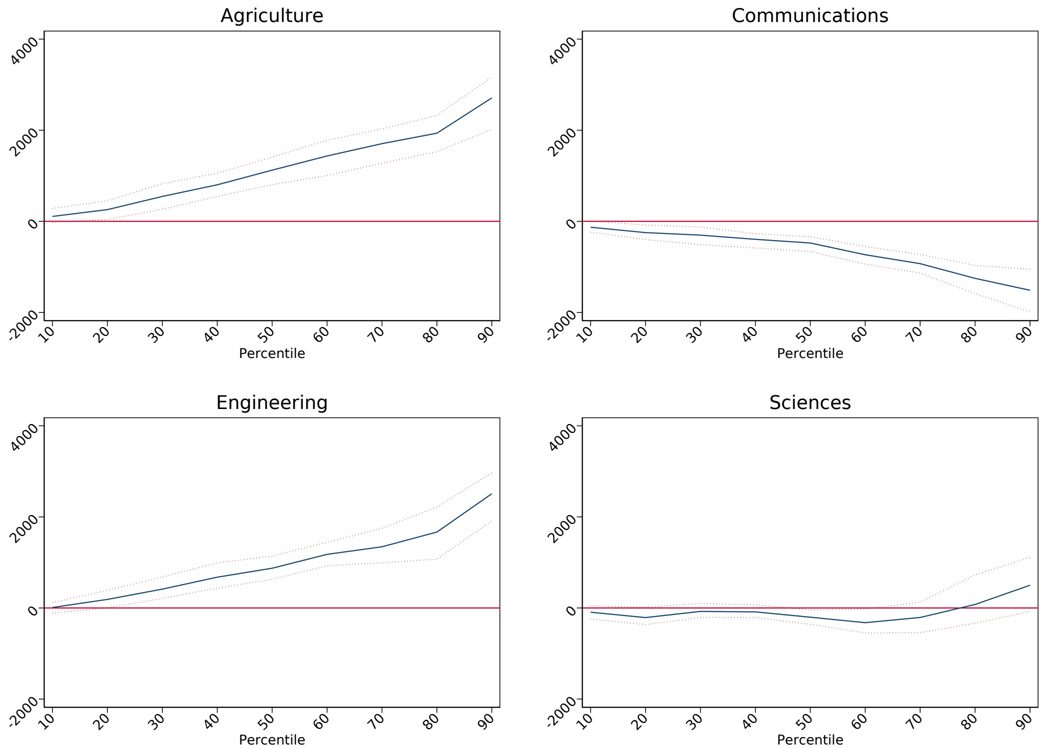


Figure A-4: Quantile Treatment Effects of Major on Average Quarterly Earnings - 4-year Students, Smaller Fields



Notes: All estimates are relative to liberal arts majors and 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 dots show the 95% confidence interval, calculated using a black bootstrap at the postsecondary institution level.

Figure A-5: Quantile Treatment Effects of Major on Average Quarterly Earnings - 2-year Students, Smaller Fields



Notes: All estimates are relative to liberal arts majors and 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 dots show the 95% confidence interval, calculated using a black bootstrap at the postsecondary institution level.