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

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ABSTRACT

There is a growing body of research examining the labor market returns to college major, which is motivated by the strong growth in the 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. We use linked administrative data from Texas on public K-12 students, public higher education students, and quarterly earnings from the unemployment insurance system to estimate the return to college majors, controlling for a rich set of pre-collegiate achievement measures, student demographics, and high school and college fixed effects. Our study focuses on several main gaps in the literature. First, we estimate how the returns to majors change over time as workers gain experience. We find that majors are associated with varying earnings growth, which makes the returns sensitive to the experience distribution of the analysis sample. Second, we move beyond the mean and estimate how average earnings effects vary across workers. We estimate quantile treatment effects of college major on earnings, showing that mean effects mask considerable heterogeneity. Third, we leverage the quarterly frequency of our earnings data and estimate how field choice affects the coefficient of variation in earnings. Finally, we show that college major effects on earnings levels and on the coefficient of variation are negatively correlated, indicating that high return majors are even more beneficial because they also have more stable earnings over time.

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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 toward services. Even middle class jobs require some postsecondary education, and substantial postsecondary education is necessary to access 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 time 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 average return to collegiate training. But the average return masks important heterogeneity across a number of dimensions (Lovenheim and Smith 2021), 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 a large amount of variation in earnings across students with different majors (Arcidiacono, 2004; Hamermesh and Donald, 2008; Altonji, Blom and Meghir 2012; Andrews, Imberman and Lovenheim 2016; Andrews and Stange, 2019). In fact, the mean earnings differences across majors is 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 choices affect the job market prospects of college students. Furthermore, as the costs of attending college and student debt increase, providing information to students about the returns to different college majors can help them make better decisions that can increase the return to their postsecondary investment and reduce the likelihood they will default on their loans. Students are responsive to

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

this type of information when making major choices (Wiswall and Zafar, 2015, 2021), which underscores the importance of providing them with accurate information about the returns they can expect to a given major selection. Finally, understanding the returns to college major is relevant for policy-makers 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.

The prior research on the return to college majors focuses exclusively on mean effects at specific ages, and these ages vary considerably across studies. This paper sheds light on three dimensions of variation in the returns to major ignored by prior work: 1) major choices can affect the growth rate of earnings as workers age and gain experience, 2) mean effects can mask considerable cross-sectional variation across workers, which one can interpret as ex-ante risk, and 3) majors can alter the within-worker variance in earnings over time. 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 a range of students or reflect a wide range of potential 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.

To date, no research has examined how major choice affects earnings growth and the variance of earnings within and across individuals. This lack of prior work is driven by the use of smaller samples in most prior major choice analyses (especially those that focus on the US) and employing annual earnings data that do not permit one to separate earnings growth from within-worker earnings variance. Our paper additionally addresses two gaps in the literature. First, the returns to college major research has focused more on four-year students. However, the return to a given major can vary substantially across four-year (BA) and two year (AA) students. We present new evidence on the returns to majors among four-year and two-year students within the same context; prior work on the two-year sector has not examined returns alongside those in the four-year sector. Second, prior papers have focused predominantly on graduates, leaving open the question of what the return is for non-completers, including those who never declare a major. Our analysis includes this group, the importance of which 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 in Texas using administrative data linking all public K-12 students to higher education records among those attending a public postsecondary institution in Texas 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 first attending a four-year and a two-year college, aggregating majors into the following groups: engineering and architecture, business and economics, information technology (IT), physical sciences and mathematics, biology and health, agriculture, communications, social science (excluding economics), vocational, and undeclared. In the two-year sector, there also is an education major.[2] The ``undeclared'' group consists of those who do not earn a degree, however there are non-completers in each major group as well.

With these data, we perform a number of different analyses that explore the trajectory of the returns to college majors over time and the within- and across-worker variance in those earnings. First, we estimate the earnings return to college majors for three separate time periods: 5-10 years after high school, 10-15 years post-high school, and 15-20 years post-high school. These results provide non-parametric evidence on how the returns to different majors change with worker experience. Second, we provide semi-parametric evidence on how changes in returns vary over the early part of a worker's career by estimating models with linear splines in the return to experience. We allow there to be a separate intercept at 5, 10, and 15 years as well as different slopes in the return to experience between 5-10, 10-15, and 15-20 years after high school. Third, we examine the cross-sectional variance in earnings returns across workers by estimating unconditional quantile treatment effect models that employ all earnings observations (DiNardo, Fortin, and Lemieux 1996; Firpo 2007). These estimates provide new evidence on

[2] Texas public universities do not offer four-year undergraduate degrees in education.

how major choice affects the distribution of earnings. Fourth, we estimate the within-worker variance in earnings by estimating the coefficient of variation (CV) relative to predicted earnings for each worker. In our preferred approach, we estimate predicted earnings by allowing for an individual intercept and linear slope (i.e., growth trajectory) for each worker. We also probe the sensitivity of our results to using 2- and 4-quarter moving averages on each side of the focal quarterly earnings observation to measure predicted earnings. Taken together, our results substantially extend our understanding of how major choice influences labor market outcomes beyond mean earnings, allowing us to provide a more complete picture of the return to field of study.

Throughout this analysis, we employ selection on observables methods using the rich pre-collegiate and collegiate data to which we have access, and we estimate the return to each major relative to liberal arts. The data allow us to account for important measures of pre-collegiate test scores and student demographics that have been used in some (but not all) prior studies of the returns to college major. We also are able to extend the control set by including 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 the 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 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, and it would be infeasible to estimate the distributional effects on which we focus with RD models.

Our findings are numerous and are difficult to summarize succinctly. We will instead discuss some broad findings and conclusions from our study. We find that the returns to college major vary over time since high school in heterogeneous ways across majors. The relative return to a four-year biology and health or economics and business degree doubles or triples across the 5-10 to the 15-20 experience ranges, while relative returns to agriculture, communications, and social sciences decline substantially with experience. Among two-year students, the returns to several degrees are positive relative to liberal arts 5-10 years after high school, but by 15-20 years the relative returns are all strongly negative. These results underscore the importance of timing and the high relative long-run return to a liberal arts AA degree.

The results further point to important differences in the variance of returns both cross-sectionally and within-worker. The quantile treatment effect estimates 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 earnings effects embed substantial (and differential) ex-ante risk for students. We additionally show that college majors have a modest effect on the coefficient of variation within worker. Most estimates are negative, indicating that 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 in years 15-20 is negatively correlated with the effect on the coefficient of variation. This finding suggests that the high returns majors also have lower earning variability, making them even more desirable to students.

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, and how majors influence the within-worker variance in earnings. We do so using rich administrative data that allows us to control more extensively for selection into different majors. Taken together, our results highlight the importance of understanding these various dimensions of the return to college major in order to help students, policymakers, and higher education administrators make more informed decisions about in which major to enroll and where to allocate resources.

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 (2021) discuss 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; Carnevale, Cheah, and Hanson, 2015; Hershbein and Kearney, 2014). 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 are likely to major in technical areas, such as economics and STEM fields, have higher pre-collegiate math 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. 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.[3] These studies use national surveys to estimate returns to major and often are able to account for many observed pre-collegiate characteristics of students. The set of characteristics on which they focus varies across studies, and none of which we are aware is able to control for high school and college fixed effects. 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 growing set of studies exploits 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, forthcoming). This approach is motivated by concerns that even a rich set of controls may be insufficient to fully account for selection into majors. The results from this research tell 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

[3] See Altonji, Blom, and Meghir (2012) and Altonji, Arcidiacono, and Maurel (2016) for a review of selection on observables studies.

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 the existence of GPA cutoffs for major access is not ubiquitous. These analyses also focuse 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 through the use of individual fixed-effects. Jepsen, Troske and 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 heath degrees.[4] This literature necessarily focuses on older students who have labor market experience prior to school, making comparisons difficult to the studies focused on the four-year sector.

We make several contributions to this literature. All of the papers discussed above focus on mean effects and use workers with different levels of experience. For example, Arcidiacono (2004) studies workers 14 years after high school (approximately 32 years old), Kirkebøen, Leuven and Mogstad (2016) examine workers 8 years after college application (around 26 years old), Andrews, Imberman, and Lovenheim (2017) pool workers from their early 20s up to age 36, and Bleemer and Mehta (forthcoming) observe earnings at most 10 years after college enrollment. If there is heterogeneity in the earnings paths associated with different college majors, these studies will have different findings just from differences in the age groups studied. This makes it challenging to compare across studies without a more complete understanding of how college major choice affects the return to experience.

Hershbein and Kearney (2014), Webber (2014, 2016), and Martin (2021) provide some evidence on variation in the returns to major across the lifecourse.[5] Hershbein and Kearney (2014) use ACS data to show median lifetime earnings and earnings trajectories by major. However, the ACS data do not include pre-collegiate controls, so these patterns are more

[4] Lovenheim and Smith (2021) and Altonji, Arcidiacono, and Maurel (2016) review the RD analyses, while Lovenheim and Smith (2021) reviews the literature on the return to AA degrees and sub-baccalaureate certificates and diplomas.

[5] Kim, Tamborini, and Sakamoto (2015) also examine how the return to postsecondary education varies over the lifecycle, 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.

descriptive in nature. Webber (2014, 2016) conducts simulations of lifetime returns to different majors by combining National Longitudinal Survey of Youth and American Community Survey data. He accounts indirectly for selection into college majors based on cognitive and noncognitive skill measures by estimating the extent to which the major coefficients change in the NLSY79 when these skill measures are included in the regression. He then manually adjusts the earnings premia in the ACS using these differences. His results indicate differential growth in earnings over the early career (ages 25-40), however he only has 4 major categories and relies on the assumption that the selection process underlying the ACS data is similar to the selection process in the NLSY79 data. Martin (2021) uses a unique data merge between the ACS, the National Survey of College Graduates (NSCG), and the Longitudinal Employer Household Dynamics 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. Much of the reduction in the gap can be explained by workers switching occupation and employer.

Our work extends this prior research by explicitly modelling how the return to major varies across the early career, allowing the return to major to vary flexibly with experience. We are able to control richly for student background characteristics using the same sample as our outcome data, and our sample size is sufficiently large that we can examine 10-11 major categories as well as include students at two-year and four-year colleges.

In addition to adding to the literature on how the return to major varies with experience, a major contribution of our work is to move beyond the examination of mean effects. None of the papers described above examine distributional effects or earnings volatility. The mean earnings impact of major choice misses the fact that mean effects 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 risk in terms of the likelihood a randomly chosen student actually obtains that level of earnings. If high mean earnings returns come with substantial risk, it reduces the long-run benefits of specific majors. Andrews, Li and Lovenheim (2016) find evidence of substantial cross-worker earnings variance with respect to college quality. 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. No research has examined this question with respect to college majors in detail. To our knowledge, the only prior analysis of distributional effects within majors is Schanzenbach, Nunn, and Nantz (2017), who investigate raw differences in median earnings within major fields but across occupations.

The vast majority of the existing research on returns to majors uses annual data, and the ones that use quarterly earnings data do not exploit the within-year variation in earnings directly. Hence, no work has been done that addresses the potential for major choice to generate variation in earnings within individuals.[6] 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. 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 their 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 volatility. 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. To date, no research has examined how major choice is related to earnings variance within individuals over time.

This paper provides novel evidence on distributional effects and impacts on the volatility of earnings from major choice. Given the substantial amount of risk aversion in occupation choice found by Dillon (2018) and the strong link between majors and occupations (Kinsler and Pavan 2015; Leighton and Speer 2020; Li, Linde, and Shimao, 2021), it is important to provide accurate information to students about distributional and earnings volatility effects of major choice. Our paper presents the first such evidence in the literature.

III. Data and Sample

a. Data and Analysis Variables

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

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.[7] The quarterly nature of these data as well as the large sample size of workers allow us to move beyond measures of mean earnings at a given time period to examine the distribution of earnings, the within-worker variance of earnings, and changes in earnings with age/experience.

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 each degree was earned from each institution. Higher education records exist for both completers and non-completers, and both groups are contained in our analysis sample. These data contain all students who enroll 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 the vast majority of college students. We classify students based on where they first enroll in college if they do not transfer across levels. If a student transfers, we classify them according to the highest degree they earn or the most recent college at which they were enrolled before dropping out. 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.

Labor market outcomes are constructed from quarterly earnings records through 2017 for each student who remains in Texas, with the exception of those working for the Federal Government and those who are self-employed. To be in the earnings data, one must be working in the State of Texas. Thus, we cannot distinguish between those who are unemployed, are not in

[7] The earnings data also exclude individuals employed by the Federal government, including the US Armed Forces and US Postal Service, and the self-employed.

the labor force, or are working outside of Texas. 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, 2019). 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 low out-migration (Foote and Stange, 2019).

Our main analysis sample includes all 2-year and 4-year Texas public college attendees who graduate from a Texas public high school from 1996 through 2002. 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, including records from those who have permanently left the state (and thus do not show up in the earnings sample). While addressing out-migration bias, this approach will tend to ignore any impacts of college major on employment immediately after college or at the end of our analysis window. We also exclude quarters in which students are enrolled in a postsecondary institution, which ensures we are not attributing low earnings during graduate school enrollment to a specific major. All earnings are converted to 2016 dollars. For computational tractability, we collapse the data to use average individual earnings that qualify for inclusion into the sample and that are in the specified experience range. The sample sizes reported in the tables thus reflect the number of individuals, not the number of quarterly observations.

We place four-year students into one of 11 major group: agriculture, communications, IT, vocational, engineering and architecture, biology and health, physical sciences and math, social sciences (excluding economics), business and economics, and undeclared. For two-year students, we also include an education major, however there is no such major offered by Texas public four-year colleges. Students are classified based on their last observed major. For graduates, this is the major of the degree they earned, and for non-completers it is the last observed major prior to dropping out. None of those with an "undeclared" major has a college degree, and many students with a declared majors also do not complete a degree.

Table 1 presents descriptive statistics for the analysis samples, including the proportion of students majoring in each field. 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 24.2 and 34.2 percent, respectively, in the two-year and four-year sectors. Biology and health also is popular in both sectors. Majoring in social science, business and economics, communications, and 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. A very small portion of the sample double majors. For these students, we code them as majoring in both subjects.

Online Appendix Table A-1 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 variation in earnings across majors reflects these differences in the characteristics of students, which highlights the importance of controlling as richly as possible for the composition of students in each major.

b. Measuring the Coefficient of Variation

In order to construct the coefficient of variation, we need a measure of expected earnings around which quarterly earnings can vary. In our preferred approach, we do so by decomposing earnings 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. The individual-specific intercept and slope comprise the predicted part of earnings, and the residual is then used to estimate the coefficient of variation.

Specifically, the earnings of individual *i* during time *t*, denoted Y_{it}, can be written as the sum of these three components:

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

where

$$\tilde{Y}_{it} = Y_{it} - (\alpha_i + \beta_i t). \quad (2)$$

Hence, $\tilde{Y}_{it}$ is the residual with respect to the linear predicted earnings model. We define $\widehat{Y_{it}} = \alpha_i + \beta_i t$ as the predicted earnings in any quarter (t) from this model. *Individual*-specific intercepts and growth rates for our sample are estimated via OLS separately for each individual, using the 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. Instead, we estimate 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-2.

Online Appendix Figure A-1 shows the average earnings by time since high school graduation for several fields. The raw growth patterns over this time period are approximately linear, which helps justify the use of a linear growth parameter. Other fields show approximately linear growth as well. We are restricted to linear individual growth profiles due to computational tractability. To provide some evidence on the robustness of our results to alternative ways of predicting earnings, we also use a 2-quarter and 4-quarter moving average (MA) on each side of the focal observation. For example, if the observation is Q1 2010, we would predict earnings using quarters 3 and 4 of 2009 and quarters 2 and 3 of 2010 for the 2-quarter MA and would use quarters 1-4 of 2009 and quarters 2-4 of 2010 and quarter 1 of 2011 for the 4-quarter MA. While these more flexible approaches to predicting earnings attenuate our estimates, the broad pattern of results are robust to the use of these multiple measures. The conclusions we draw from this analysis thus are not driven by a particular earnings prediction model.

Our preferred measure of earnings volatility at a point in time is the absolute value of the deviation of actual from predicted quarterly earnings, divided by the predicted value. This is the coefficient of variation: $\widehat{CV}_{it} = \frac{abs(Y_{it} - \hat{Y}_{it})}{\hat{Y}_{it}}$. This can be interpreted as 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 volatility and a larger CV. A negative effect on the CV indicates that a major exhibits lower earnings volatility than the base major.

IV. Empirical Methodology

a. Linear Model

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

$$Y_{icsjk} = \mu + \boldsymbol{\theta_k} \mathbf{1}(Major_i = k) + \boldsymbol{\Omega X_i} + \delta_{cs} + \gamma_{cj} + \epsilon_{icsjk} \quad (3)$$

where Y_{iscjk} is an outcome for individual i, from high school s, in high school cohort c, attending postsecondary institution j, and majoring in field k. We estimate models separately by sector (4-year vs. 2-year). The coefficients of interest in equation (3) are the $\boldsymbol{\theta_k}$, which are the estimates on each of the field of study indicators. 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 *ex-ante* outcome differences, inclusive of any effects operating via degree completion.[8] 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 in the model are sufficient to account for the non-random sorting of students into majors. This is admittedly a strong assumption, however it is rendered more palatable by the extensive set of controls in the model. We control for a number of measures of pre-collegiate academic aptitude: standardized 11$^{\text{th}}$ grade math and reading test scores that one must pass in order 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 class in each high school to any college in Texas. Student rankings 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% plan. Hence, we include these measures in our empirical model as controls. 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 some of the most high-quality prior selection-on-observables studies use in their models. Our large sample sizes and rich data also allow for two other sets of controls: high school by cohort fixed effects and college by cohort fixed effects. Cohort is defined as the high school graduating cohort. Because of geographic sorting and patterns of segregation by race/ethnicity and SES, one's high school

[8] We categorize students by last major before degree completion or drop-out, rather than first major, so our estimates are not strictly ex-ante to major choice to the extent that initial and final major differ.

incorporates much information about one's background. Furthermore, college and major can have independent effects on earnings (e.g., Kirkebøen, Leuven, and Mogstad 2016), but major choice and college choice can be correlated with one another. 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, and they increase the credibility of our selection on observables approach. While we are unable to test the main identifying assumption of no selection on unobservables conditional on the 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. Since these controls are new, we show the effect of adding them into the model relative to the more traditional controls.

b. Quantile Treatment Effects

To identify the effect of college majors on the cross-sectional distribution of earnings, we estimate unconditional quantile treatment effect estimates (DiNardo, Fortin, and Lemieux 1996; Firpo 2007). We closely follow the approach used in Andrews, Li, and Lovenheim (2016) to 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:

$$I(k)_{icsj} = \zeta + \mathbf{T}\boldsymbol{X_i} + \omega_{cs} + \phi_{cj} + \nu_{icsj}, \quad (4)$$

where all other variables are as previously defined. For each non-liberal arts major, we estimate a separate version of equation (4), and the predicted values from these logit models are used to construct the following weights:

$$\psi(x) = \frac{P(K = k|x)}{1 - P(K = k|x)}. \quad (5)$$

Equation (5) is the odds ratio of the conditional likelihood of 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.[9] 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 method relaxes the linearity assumption in OLS models, but conceptually both methods are identified under the assumption that the observed characteristics are sufficient to account for the selection of students with different potential earnings into different majors. [10] We also highlight that under the selection on observables assumptions the QTE 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.[11] 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. While beyond the scope of our analysis, this highlights the importance of these QTE estimates.

V. Results

a. Mean Earnings Effects of College Major and Earnings Trajectories

Figure 1 present the estimates of θ_k from equation (3), separately for years 5-10 (panel a), 10-15 (panel b), 15-20 (panel c) among four-year students. The black triangles show estimates without controls but with cohort fixed effects, the green squares show the estimates that include the controls 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 (3). The point estimates and standard errors for all of these models are shown in Table 2.[12] The standard errors tend to be

[9] This method is akin to the aggregate decomposition described in Fortin, Lemieux, and Firpo (2011).
[10] One subtle difference is that by estimating (4) 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 (3) constrains the coefficients to be equal across majors. The QTE estimates thus also permit controls to enter more flexibly.
[11] 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 strong assumption that is unlikely to be met in this context.
[12] Because we use average individual earnings that qualify for sample inclusion and that are in the specified experience range, the number of observations in the tables reflect the number of individuals rather than the number of quarterly earnings observations.

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.

Panel c of Figure 1 and column (9) of Table 2 show that 15-20 years after college, our preferred model produces large average differences across majors. Engineering and architecture has the highest returns relative to liberal arts, at $7,769 per quarter, with business and economics ($6,593), biology and health ($5,719), and IT ($4,583) also experiencing high relative returns. Average quarterly earnings in this sample is $16,690, so these effects are large relative to the mean. Agriculture ($1,143), communications ($882), and social sciences ($434) have the lowest returns. All estimates are positive and statistically significantly different from zero at the 5% level, so on average 15-20 years after high school liberal arts majors earn less than other majors among four-year students. Interestingly, undeclared students, none of whom have a four-year degree, also earn $1,692 more on average per quarter than liberal arts majors.[13] This is an important finding that points to substantial returns to sub-baccalaureate training among college non-completers.

Figure 1 and Table 2 also show the importance of the controls we use, especially the novel high school-cohort and college-cohort fixed effects. We note three important patterns with these results. First, the controls matter differentially for different majors. For example, the engineering and architecture estimates 15-20 years after high school are cut almost in half, from $14,260 to $7,769, when going from the "no controls" to the most saturated specification. This general pattern holds across all time periods, but the selection effect grows with experience. Physical sciences and math, IT, and agriculture estimates also are substantively attenuated by the controls. Conversely, the estimates for social sciences, undeclared, vocational, and communications are less sensitive 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 attenuate the estimates, and the pattern of effects of the controls are similar over time. 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. These fixed effects become more important for more experienced workers, suggesting that some of the residual selection bias is expressed in the form

[13] While we track individual that transfer between public institutions in Texas, non-completers may also include students that transfer from a Texas public institution to either private or out-of-state institutions.

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.

The final pattern of note in Figure 1 and Table 2 is the large and differential changes with experience in the returns to field of study. To facilitate comparisons over time, we plot estimates using our preferred specification for all three time periods together in Figure 2. Several fields exhibit substantial growth in returns over time: biology and health returns increase from $1,473 to $5,719 over time, engineering and architecture increases from $4,486 to $7,769, physical sciences and math increases from $1,585 to $3,119, and business and economics increases from $3,497 to $6,593. It is likely that much of this growth reflects investments in graduate school and subsequent sorting of these students into high-paying professions.[14] 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. They never become negative, however. The return to being undeclared is stable over time, which suggests a modest return to sub-baccalaureate non-degree training that does not change with experience. 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 cause rank switching as workers gain experience. This will lead to heterogeneity across papers based only on the experience composition of the sample.

Figure 3 and Table 3 present analogous estimates among two-year students. Similar heterogeneity is evident as in the four-year sector, although the specific patterns across majors differs. This highlights the value of examining two-year students directly. Panel (c) of Figure 3 and column (9) of Table 3 shows that the relative returns to major all are negative. The estimates are statistically significantly different from zero for all but undeclared and vocational, but the latter estimate is significant at the 10% level. Recall that these returns are relative to liberal arts majors, which emphasizes the relatively high return to a two-year liberal arts degree 15-20 years after high school. As with the two-year sector, there is a wide variation in relative returns across

[14] 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.

majors. Communications, agriculture, social sciences, education, and IT all exhibit negative relative returns of over -\$2,000, with the penalty for communications being particularly large at -\$3,090. Average quarterly earnings among 2-year students is \$12,105 15-20 years after high school, so these effects are sizable when compared to the mean. Vocational and undeclared majors experience the smallest gap with liberal arts, at -\$354 and -\$272, respectively. Biology & health and business & economics also have negative returns less than \$1,000. That the longer-run return to liberal arts AA degrees is so large relative to other fields is a novel finding in this literature.

As in the four-year sector, Figure 3 and Table 3 show 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 social sciences, communications, and education in all three time periods, the controls lead to sizable increases in the returns. This is evidence of adverse selection into these majors. It is important to note that we see no evidence of such selection in the four-year sector, which underscores the value of examining these patterns separately for two-year students. That the patterns of selection into majors vary across two-year and four-year students has not been documented before in the literature. 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.

Figure 3 and Table 3 show that liberal arts students earn more than those in other majors 15-20 years after high school. The relative value of liberal arts changes substantially over time, however, as shown in Figure 4. In the two-year sector, the variation in returns by experience is even more stark than in the four-year sector. Vocational, undeclared, biology & health, and business & economics majors all experience positive and sizable relative returns 5-10 years after high school, as shown in Figure 3 panel a and in Table 3. Even 10-15 years after high school the returns for these majors other than business and economics are still positive though attenuated. As previously discussed, by years 15-20, all of the estimates are negative. The positive, large return to vocational degrees aligns with prior literature showing that high average returns to vocational two-year degrees (Lovenheim and Smith, 2021). The evidence that liberal arts majors catch up and surpass them is novel. This pattern may reflect that prior work has focused on older students with pre-college work experience. Our results also point to relatively high returns for undeclared students, who do not finish a degree.[15] It is not clear why those without a degree earn more than those who graduate, but these results suggest on average low returns to completing a community college degree.

Figures 2 and 4 indicate 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 trajectory of earnings. We estimate a version of equation (3) that allows for piecewise linear growth in earnings across majors. There is a separate estimated intercept for years 5, 10, and 15 as well as separate quarterly linear growth rates between years 5-10, 10-15, and 15-20. These results show the relationship between college major and the trajectory of earnings and provide some insight as to whether returns stabilize after 20 years.

Figure 5 presents these estimates for four-year students and Figure 6 presents them for two-year students. Focusing on Figure 5, there is substantial growth in business & economics, biology & health, and engineering over time. The patterns differ, with business & economics returns exhibiting linear growth, biology & health showing more growth after 15 years, and engineering returns rising more in years 5-10. Agriculture, IT, communications, vocational, and social science have relative returns that rise in years 5-10 but then decline thereafter. Those with undeclared majors have higher early returns that decline over time, likely because those with degrees catch up as they gain experience and potentially earn more advanced degrees. Again, these results demonstrate the importance of accounting for earnings trajectories and the age of the sample when examining the returns to majors. Returns change considerably as workers gain experience. The slopes in the 15-20 year period are non-trivial for many majors, suggesting that relative returns will continue to change beyond 20 years after high school.

Analogous estimates for two-year students are shown in Figure 6. There is far less variation across majors than was evident in the four-year sector, although there are some notable strong trends in relative returns. Outside of engineering & architecture, the curves all slope downward, often rather strongly. The return to agriculture relative to liberal arts declines steeply after 15 years, while the slopes for the other majors are more modest and are linear. That they do

[15] Kane and Rouse (1995) is one of the only prior papers to examine the returns to college credits that do not lead to a degree. They find evidence that among men and women there is a return to 2-year college credits among non-degree recipients, but in the four-year sector such returns are only evident for women.

not flatten out suggests that liberal arts majors will continue to gain ground on other two-year students as they obtain more experience. Engineering and architecture also has a negative slope until year 15, at which point the slope becomes positive and large. On average, returns are lower in years 15-20 than in years 5-10 (as shown in Figure 4), but the average misses this upward trajectory. These results are suggestive that the relative returns for engineering and architecture majors will turn positive after 20 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 in prior work. 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

Little prior work goes beyond estimating average 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 actually obtains that level of earnings. If mean earnings returns come with substantial risk, it reduces the benefits of specific majors, especially if students are risk averse. No research has examined this question with respect to college majors.[16]

We estimate quantile treatment effects 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 7 shows QTE estimates for each field of study among four-year students. 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 QTE for each decile from

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

10-90. 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, IT, business & economics, biology & health, and physical sciences & math all 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 are negative, but the largest returns to these majors flow to those at the top of the distribution. There thus 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, vocational, social science, and undeclared majors. For these majors, only the top of the earnings distribution shifts out. Hence, these positive average returns are driven 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 the 20th to the 70th percentiles of the distribution among undeclared students. The mean effects present a misleading picture of the earnings returns to these majors.

Figure 8 presents QTE estimates among 2-year students. The specific patterns across majors differs from those in the four-year sector, but the main takeaway that the mean masks important distributional effects is similar. The effect on the earnings distribution increases approximately linearly for agriculture, engineering & architecture, vocational, and undeclared. Conversely, the QTEs are strongly negatively sloped for social science, education, and communications majors. This means that the earnings penalties associated with these majors relative to liberal arts are particularly large among higher earners. The QTEs are flat among physical sciences & math, business & economics, IT, and biology & health majors. For these majors, the average estimates are representative of what students can expect to earn. Among the other majors, Figure 8 shows that the mean effects come with substantial ex-ante risk. That majors differ in the slope of these QTEs suggests that in some cases those bearing this risk are higher earners and in some cases they are lower earners.

c. Within-person Earnings Variability

Little prior work has 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 4 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. Columns (3)-(4) show results that use a 2 quarter moving average on each side of the focal quarter, and columns (5)-(6) present estimates using a 4 quarter moving average.

We focus on the estimates in column (2), which are from our preferred model and include all controls. A negative estimate indicates that earnings are less variable relative to liberal arts majors. The point estimates are universally negative and are statistically different from zero at the 5% level. The effects range from -0.056 for social sciences to -0.167 for business & economics. Most of the estimates are between -0.100 to -0.167, which is not a large range. These estimates point to liberal arts majors experiencing more within-person variability than other majors, with more minor variation in earnings instability across other majors.

The estimates are not particularly sensitive to the inclusion of controls, but the effects are significantly attenuated when using the 2-quarter and 4-quarter moving averages. This is unsurprising, as these moving average 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 -0.006 (undeclared) to -0.059 (IT) and continue to be statistically significant at the 5 percent level. In column (6), the estimates range from -0.031 (social sciences) to -0.128 (IT) and all are significant 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.

Effects of college major on the coefficient of variation among 2-year students are shown in Table 5. The estimates in column (2) are much smaller than their counterparts in the four-year sector, ranging from -0.069 (undeclared) to 0.036 (engineering and architecture). All but five of the estimates are significant at the 5% level, and only the estimate for engineering and architecture is positive (but not significant at even the 10% level). The moving average models produce even more attenuated effects, ranging from -0.012 (undeclared) to 0.024 (engineering and architecture) in column (4) and from -0.044 (undeclared) to 0.040 (engineering and architecture) in column (6). The engineering and architecture and social science estimates are positive and statistically significant at the 5% level in column (6). Unlike in the four-year sector, some two-year majors exhibit more earnings variability than liberal arts. The point estimates are small for two-year students, suggesting little return to major in terms of earnings variability.

d. Correlation Between Average Earnings and CV Effects

In order to more fully characterize the returns to college major, 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 reinforce one another, 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 opposite direction it indicates a tradeoff between the earnings level and variability.

Figure 9 shows these correlations for four-year students (panel a) and two-year students (panel b). The mean estimates come from column (9) of Tables 2 and 3 (i.e., the estimates for years 15-20), and the CV estimates come from column (2) of Tables 4 and 5. 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 -0.508 than in the two year sector at -0.354. These negative correlations indicate that the mean and CV effects reinforce on another. That is, the majors with the highest relative earnings returns also exhibit lower relative 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 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, the earnings estimates are negative, as are most of the coefficient of variation effects. Especially for some of the majors with earnings returns close to zero, the CV effects are the most negative. Hence, students may trade off slightly lower earnings with somewhat more stable earnings, making the majors in the upper left quadrant of the figure less undesirable 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.

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. 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.

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 are higher-return majors when earnings among older workers are used. We estimate models that allow for piecewise linear growth in earnings by major and show new evidence of variation not only in the mean effects across majors but in the trajectory of majors. This is important information in its own right to measure lifetime returns to major, and it also suggests that studies using workers of different ages will find different results.

Second, we move beyond the mean to estimate two forms of earnings variance. 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 variance of earnings relative to liberal arts, however the estimates in the two-year sector are much smaller than those in the four-year sector and suggest little overall effect on earnings variability.

Finally, we show how average earnings returns 15-20 years after high school are correlated with earnings variability effects. Majors with higher relative returns (or a smaller relative earnings penalty) experience larger relative reductions in the coefficient of variation. This finding suggests that higher-returns majors are even more attractive than previously thought because they also come with lower earnings variability.

Taken together, our results show the importance of moving beyond mean earnings effects at a given age to more fully 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	0.540	0.705	0.105	0.87
Reading Exam Score	0.500	0.602	0.134	0.819
Top Ten Percent Math	0.254	0.435	0.166	0.372
70th-90th Percentile Math	0.291	0.454	0.194	0.395
Top Ten Percent Reading	0.270	0.444	0.189	0.392
70th-90th Percentile Reading	0.290	0.454	0.201	0.4
Male	0.443	0.497	0.466	0.499
White	0.623	0.485	0.530	0.499
Hispanic	0.227	0.419	0.314	0.464
Black	0.098	0.298	0.125	0.331
Asian	0.049	0.215	0.028	0.166
At Risk	0.183	0.386	0.360	0.48
Economically Disadvantaged	0.171	0.376	0.263	0.44
Earnings 5-10 Years Post-HS	6,699	6,239	5,760	5,274
Earnings 10-15 Years Post-HS	12,248	12,737	9,078	8,605
Earnings 15-20 Years Post-HS	16,690	16,476	12,105	12,251
Liberal Arts	0.242		0.342	
Agriculture	0.038		0.006	
Communications	0.054		0.006	
IT	0.017		0.034	
Vocational	0.087		0.139	
Engineering + Architecture	0.062		0.008	
Biology + Health	0.100		0.143	
Physical Sciences + Math	0.022		0.005	
Social Sciences	0.124		0.034	
Business + Economics	0.221		0.107	
Education			0.037	
Undeclared	0.032		0.138	
Double Major	0.006		0.004	

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

	5-10 Years Post-HS			10-15 Years Post-HS			15-20 Years Post-HS		
Field of Study	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Agriculture	2,564	2,102	1,173	4,337	2,842	1,684	5,489	2,630	1,143
	(72)	(71)	(82)	(99)	(100)	(104)	(175)	(177)	(189)
Communications	1,778	1,471	1,103	2,625	2,067	1,276	3,139	2,164	882
	(44)	(43)	(43)	(92)	(88)	(86)	(160)	(150)	(141)
IT	3,950	3,504	3,474	6,875	4,582	4,578	9,232	4,778	4,583
	(98)	(100)	(96)	(216)	(201)	(193)	(309)	(273)	(254)
Vocational	2,103	2,255	2,030	3,404	2,938	2,767	3,343	2,065	2,097
	(39)	(38)	(38)	(77)	(76)	(74)	(115)	(103)	(103)
Engineering + Architecture	5,809	5,160	4,486	10,711	8,302	6,996	14,260	9,859	7,769
	(114)	(109)	(93)	(243)	(229)	(208)	(268)	(242)	(211)
Biology + Health	2,016	1,701	1,473	4,240	3,795	3,473	6,617	6,059	5,719
	(48)	(49)	(53)	(73)	(70)	(72)	(180)	(166)	(163)
Physical Sciences + Math	2,551	1,850	1,585	4,978	3,150	2,604	7,246	4,075	3,119
	(77)	(76)	(71)	(136)	(136)	(140)	(268)	(269)	(263)
Social Sciences	973	745	393	1,696	1,479	761	1,766	1,519	434
	(29)	(28)	(29)	(58)	(55)	(61)	(103)	(101)	(103)
Business + Economics	4,047	3,708	3,497	6,797	5,636	5,258	9,335	7,167	6,593
	(52)	(52)	(48)	(117)	(106)	(96)	(195)	(169)	(155)
Undeclared	1,399	1,674	2,051	1,379	1,316	1,515	1,933	1,530	1,692
	(58)	(63)	(62)	(150)	(136)	(152)	(258)	(211)	(233)
Constant	4,945	4,285	4,634	9,214	7,454	8,069	12,684	9,681	10,474
	(29)	(183)	(164)	(50)	(287)	(300)	(73)	(577)	(617)
Controls		x	x		x	x		x	x
HS-cohort & College-cohort FE			x			x			x
Observations	483,903	483,903	483,003	438,759	438,759	437,831	264,190	264,190	263,547
Dep. Var. Mean	6699	6699	6699	12248	12248	12248	16690	16690	16690

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

	5-10 Years Post-HS			10-15 Years Post-HS			15-20 Years Post-HS		
Field of Study	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Agriculture	494	168	-114	812	-171	-276	-890	-2,742	-3,010
	(217)	(215)	(243)	(419)	(407)	(434)	(549)	(524)	(566)
Communications	-971	-838	-655	-2,424	-2,287	-1,952	-3,503	-3,587	-3,090
	(130)	(131)	(142)	(222)	(228)	(238)	(443)	(459)	(479)
IT	-221	-351	-185	-1,028	-1,698	-1,298	-1,195	-2,388	-2,013
	(86)	(83)	(86)	(149)	(147)	(152)	(248)	(248)	(271)
Vocational	852	1,011	1,062	428	340	575	-286	-723	-354
	(152)	(144)	(129)	(185)	(162)	(148)	(241)	(209)	(196)
Engineering + Architecture	-76	-295	-145	-502	-1,450	-1,185	-250	-1,790	-1,326
	(159)	(152)	(157)	(258)	(252)	(265)	(622)	(613)	(642)
Biology + Health	200	466	525	-646	30	221	-2,273	-1,156	-782
	(48)	(44)	(47)	(80)	(69)	(74)	(127)	(112)	(122)
Physical Sciences + Math	-296	-548	-383	395	-243	-145	-105	-1,161	-1,158
	(168)	(165)	(171)	(367)	(357)	(357)	(555)	(530)	(539)
Social Sciences	-1,066	-677	-522	-2,304	-1,365	-1,195	-3,616	-2,135	-2,001
	(83)	(77)	(81)	(159)	(141)	(139)	(264)	(233)	(240)
Business + Economics	123	267	405	-739	-548	-229	-1,459	-1,254	-775
	(68)	(66)	(71)	(98)	(90)	(93)	(162)	(149)	(158)
Education	-943	-484	-273	-2,793	-1,798	-1,301	-4,149	-2,629	-2,136
	(69)	(67)	(69)	(118)	(110)	(117)	(290)	(271)	(201)
Undeclared	547	526	607	-115	-247	105	-366	-630	-273
	(62)	(60)	(61)	(102)	(96)	(100)	(257)	(250)	(248)
Constant	5,357	4,063	4,032	9,923	7,390	7,296	13,918	9,687	9,700
	(33)	(212)	(235)	(62)	(358)	(401)	(97)	(717)	(764)
Controls		x	x		x	x		x	x
HS-cohort & College-cohort FE			x			x			x
Observations	155,635	155,635	153,985	143,805	143,805	142,143	88,551	88,551	87,361
Dep. Var. Mean	5760	5760	5760	9078	9078	9078	12105	12105	12105

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 4: The Effect of College Major Choice on Earnings Variability - 4-year Students

	Dependent Variable: Coefficient of Variation Relative to:					
	Linear Prediction		2Q Moving Average		4Q Moving Average	
Field of Study	(1)	(2)	(3)	(4)	(5)	(6)
Agriculture	-0.144	-0.100	-0.035	-0.022	-0.083	-0.052
	(0.004)	(0.005)	(0.002)	(0.002)	(0.004)	(0.004)
Communications	-0.122	-0.112	-0.022	-0.023	-0.066	-0.068
	(0.003)	(0.004)	(0.002)	(0.001)	(0.003)	(0.003)
IT	-0.119	-0.137	-0.047	-0.059	-0.105	-0.128
	(0.043)	(0.045)	(0.002)	(0.003)	(0.006)	(0.006)
Vocational	-0.157	-0.155	-0.042	-0.044	-0.098	-0.099
	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)
Engineering + Architecture	-0.161	-0.161	-0.040	-0.045	-0.094	-0.106
	(0.003)	(0.004)	(0.001)	(0.001)	(0.003)	(0.003)
Biology + Health	-0.088	-0.068	-0.021	-0.018	-0.054	-0.048
	(0.007)	(0.007)	(0.001)	(0.001)	(0.003)	(0.003)
Physical Sciences + Math	-0.115	-0.100	-0.029	-0.029	-0.066	-0.065
	(0.005)	(0.007)	(0.002)	(0.002)	(0.005)	(0.005)
Social Sciences	-0.073	-0.056	-0.013	-0.010	-0.038	-0.031
	(0.019)	(0.019)	(0.001)	(0.001)	(0.003)	(0.003)
Business + Economics	-0.172	-0.167	-0.045	-0.046	-0.116	-0.119
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Undeclared	-0.076	-0.115	0.007	-0.006	-0.023	-0.050
	(0.006)	(0.007)	(0.002)	(0.002)	(0.005)	(0.005)
Constant	0.694	0.684	0.269	0.267	0.561	0.558
	(0.002)	(0.015)	(0.001)	(0.007)	(0.002)	(0.015)
Controls		x		x		x
HS-cohort & College-cohort FE		x		x		x
Observations	479,376	478,481	480,152	479,257	480,264	479,367
Dep. Var. Mean	0.614	0.614	0.250	0.250	0.512	0.512

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 2-quarter moving average on each side of the focal quarter, and in columns (4)-(5) we use a 4-quarter moving average on each side of the focal quarter. 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 schools level are in parentheses.

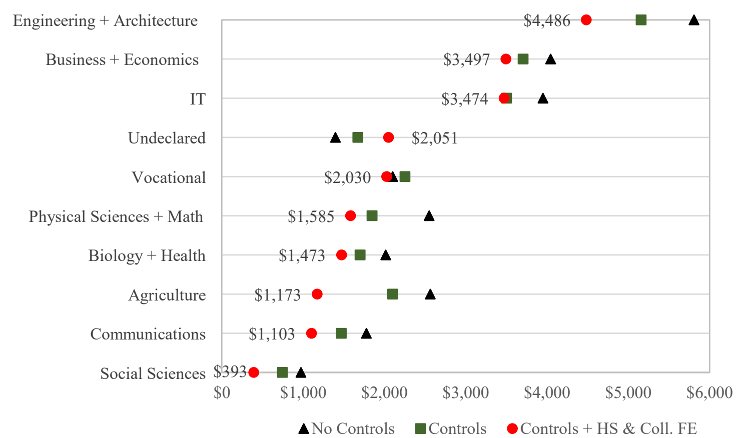
Table 5: The Effect of College Major Choice on Earnings Variability - 2-year Students

	Linear Prediction		2Q Moving Average		4Q Moving Average	
Field of Study	(1)	(2)	(3)	(4)	(5)	(6)
Agriculture	-0.062	-0.035	-0.011	0.003	-0.040	-0.006
	(0.018)	(0.021)	(0.009)	(0.010)	(0.019)	(0.022)
Communications	-0.009	-0.011	0.022	0.019	0.012	0.008
	(0.016)	(0.016)	(0.008)	(0.008)	(0.016)	(0.016)
IT	-0.029	-0.030	-0.001	-0.004	-0.020	-0.021
	(0.007)	(0.008)	(0.004)	(0.004)	(0.008)	(0.008)
Vocational	-0.053	-0.054	-0.004	-0.007	-0.035	-0.036
	(0.005)	(0.005)	(0.003)	(0.003)	(0.005)	(0.005)
Engineering + Architecture	0.035	0.036	0.026	0.024	0.045	0.040
	(0.019)	(0.020)	(0.007)	(0.007)	(0.015)	(0.015)
Biology + Health	-0.029	-0.028	-0.006	-0.005	-0.030	-0.025
	(0.004)	(0.005)	(0.002)	(0.002)	(0.004)	(0.004)
Physical Sciences + Math	-0.001	-0.002	0.003	0.003	0.003	0.003
	(0.013)	(0.014)	(0.007)	(0.007)	(0.014)	(0.015)
Social Sciences	0.004	-0.003	0.016	0.014	0.017	0.015
	(0.007)	(0.008)	(0.004)	(0.004)	(0.007)	(0.008)
Business + Economics	-0.041	-0.044	0.000	-0.001	-0.021	-0.021
	(0.004)	(0.004)	(0.002)	(0.002)	(0.004)	(0.005)
Education	-0.018	-0.025	0.007	0.006	-0.002	-0.000
	(0.008)	(0.008)	(0.004)	(0.004)	(0.008)	(0.008)
Undeclared	-0.071	-0.069	-0.013	-0.012	-0.049	-0.044
	(0.006)	(0.006)	(0.002)	(0.002)	(0.005)	(0.005)
Constant	0.692	0.738	0.293	0.311	0.592	0.624
	(0.002)	(0.022)	(0.001)	(0.010)	(0.002)	(0.021)
Controls		x		x		x
HS-cohort & College-cohort FE		x		x		x
Observations	154,708	153,054	154,878	153,223	154,955	153,300
Dep. Var. Mean	0.627	0.627	0.28	0.28	0.542	0.542

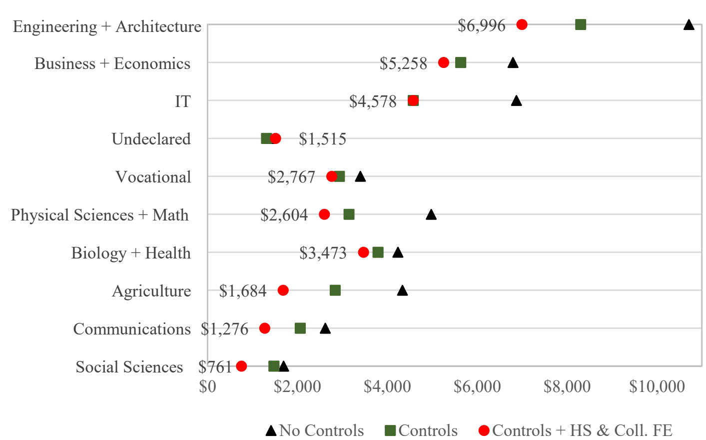
Notes: Authors' estimation as described in the text using linked administrative K-12, higher education, and quarterly earnings data from Texas. Each column is a separate regression. The dependent variable is the coefficient of variation, the calculation of which varies across columns based how wages 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 2-quarter moving average on each side of the focal quarter, and in columns (4)-(5) we use a 4-quarter moving average on each side of the focal quarter. 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 schools level are in parentheses.

Figure 1: The Return to College Majors Including Different Controls by Years After High School - 4-year Students

(a) 5-10 Years Post-HS



(b) 10-15 Years Post-HS



(c) 15-20 Years Post-HS

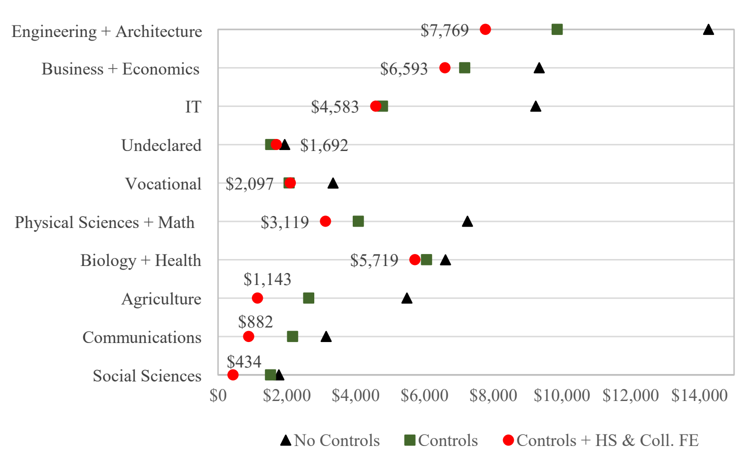
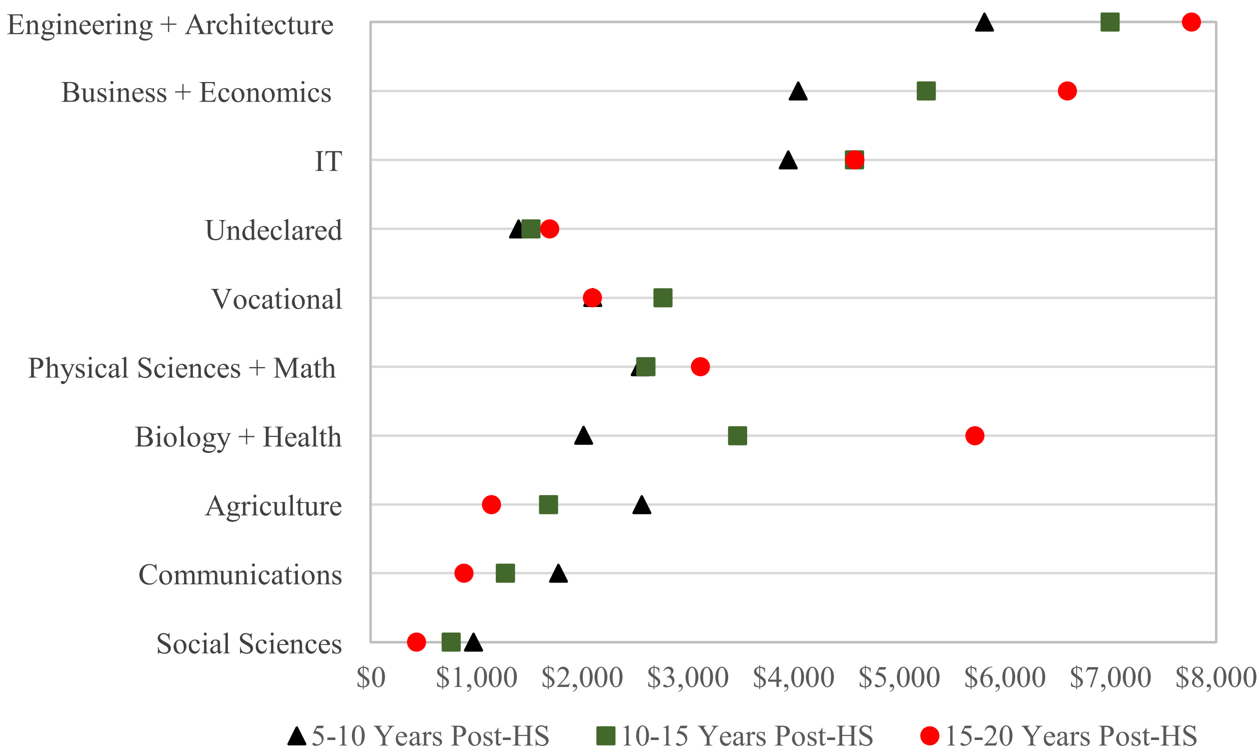


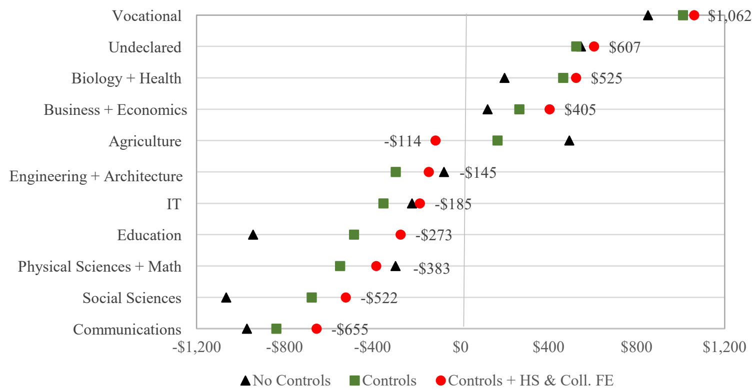
Figure 2: Change in The Return to College Majors by Experience - 4-year Students



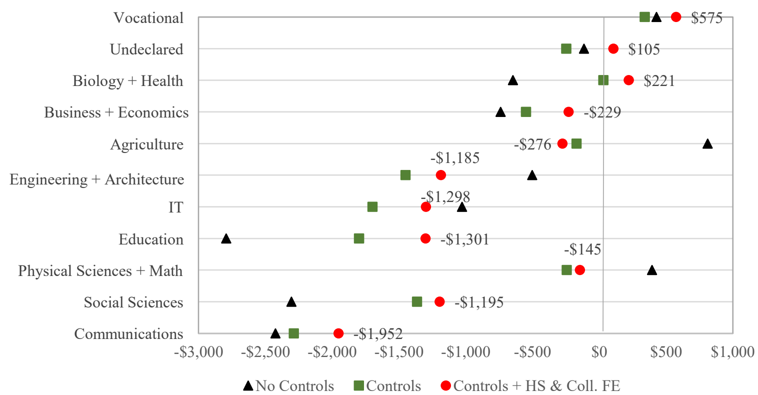
Notes: All estimates are relative to liberal arts majors and include controls for high school test scores, student demographic characteristics, HS-by-cohort fixed effects, and college-by-cohort fixed effects. Outcomes are in dollars of quarterly earnings ($2016).

Figure 3: The Return to College Majors Including Different Controls by Years After High School - 2-year Students

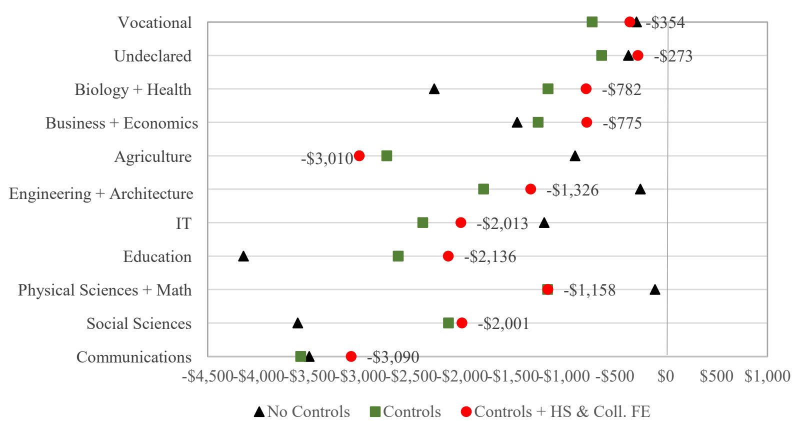
(a) 5-10 Years Post-HS



(b) 10-15 Years Post-HS

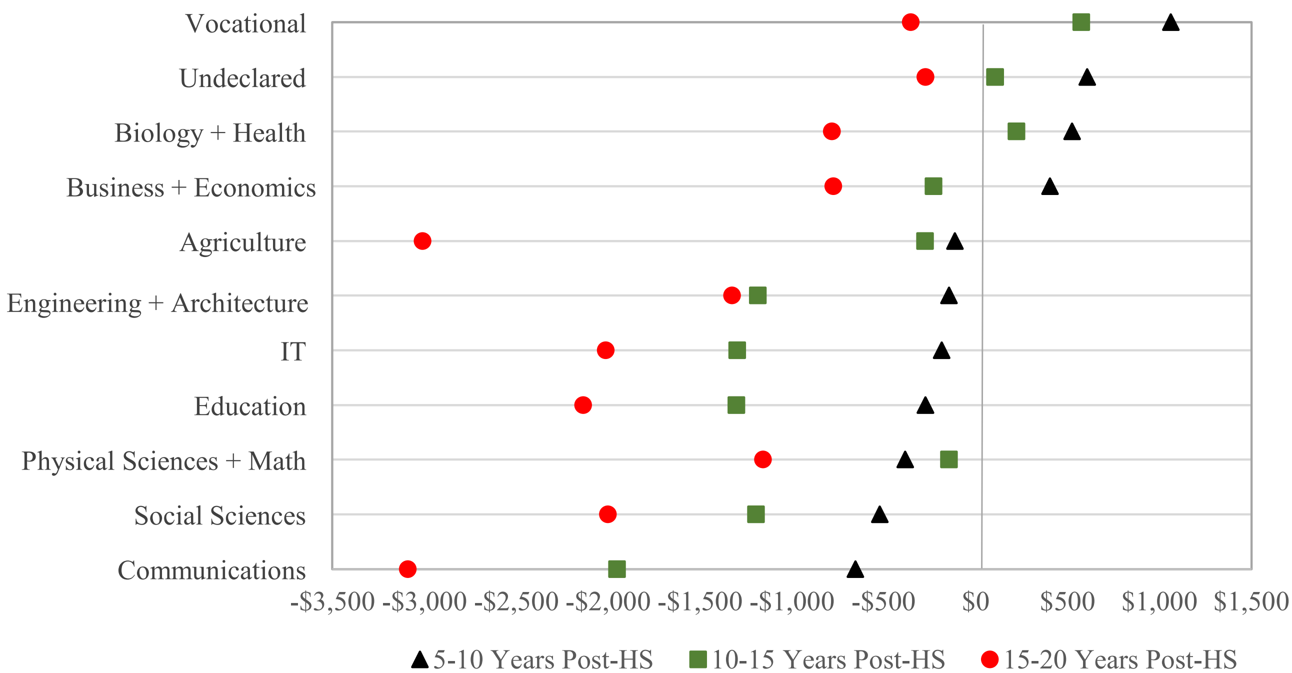


(c) 15-20 Years Post-HS



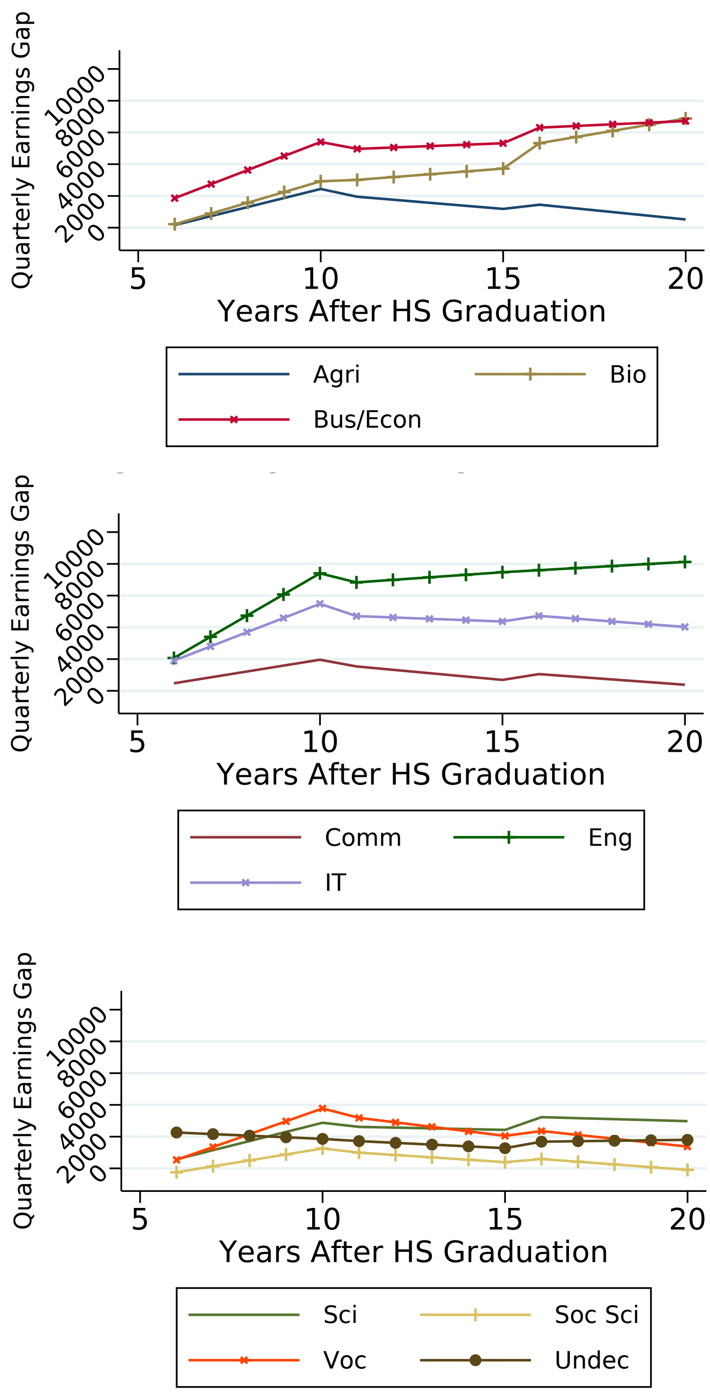
Notes: All estimates are relative to liberal arts majors. "Controls" include measures of high school test scores, student demographic characteristics, and HS cohort fixed effects. Outcomes are in dollars of quarterly earnings.

Figure 4: Change in The Return to College Majors by Experience - 2-year Students



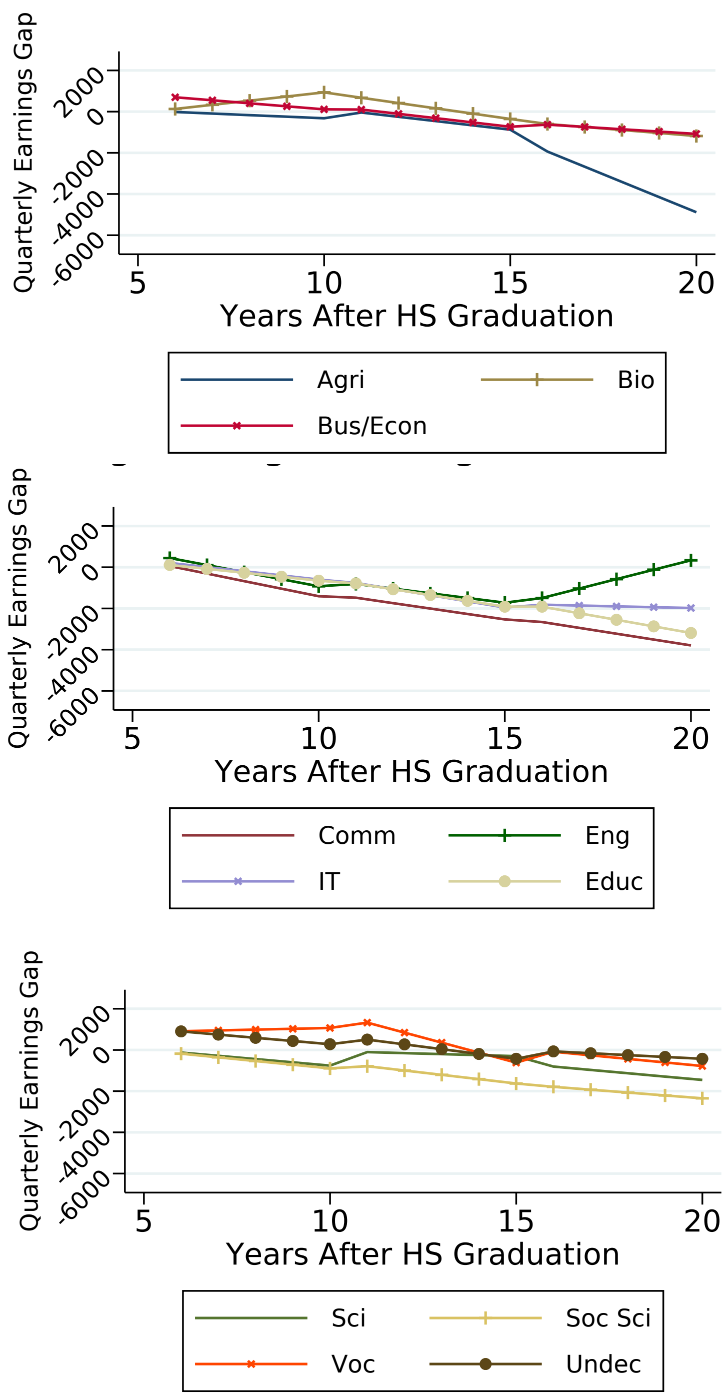
Notes: All estimates are relative to liberal arts majors and include controls for high school test scores, student demographic characteristics, HS cohort fixed effects, HS fixed effects, and first college attended fixed effects. Outcomes are in dollars of quarterly earnings ($2016).

Figure 5: Earnings Effects of Majors Allowing for Piecewise Linear Returns to 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 in dollars of quarterly earnings ($2016). Each curve comes from a piecewise linear model that allows for a separate intercept at years 5, 10, and 15 and separate linear slopes with respect to experience between years 5-10, 10-15, and 15-20.

Figure 6: Earnings Effects of Majors Allowing for Piecewise Linear Returns to 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 in dollars of quarterly earnings ($2016). Each curve comes from a piecewise linear model that allows for a separate intercept at years 5, 10, and 15 and separate linear slopes with respect to experience between years 5-10, 10-15, and 15-20.

Figure 7: Quantile Treatment Effects of Major on Average Quarterly Earnings - 4-year Students

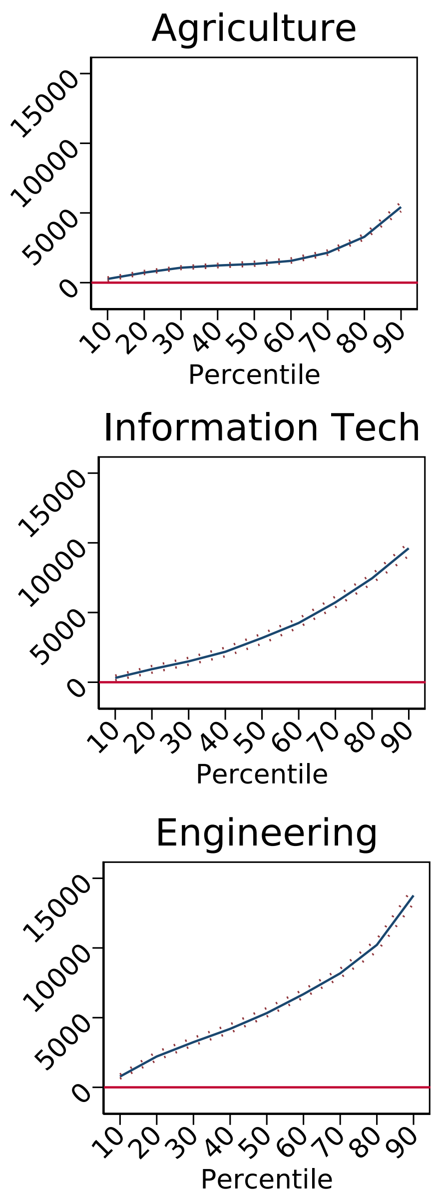
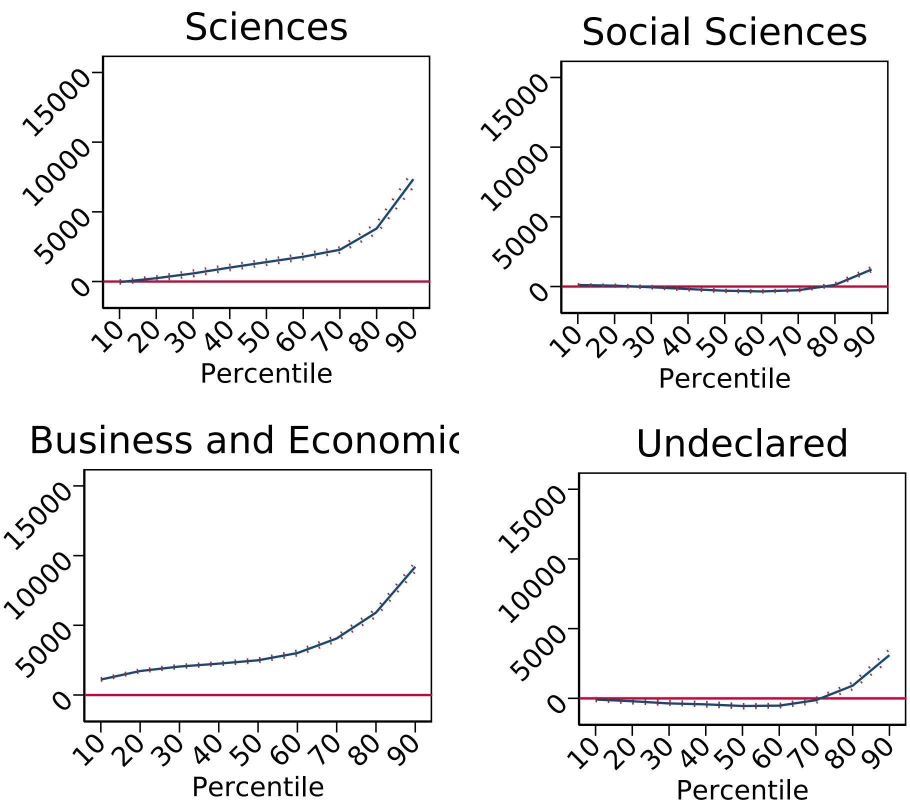


Figure 7 (cont'd): Quantile Treatment Effects of Major on Average Quarterly Earnings - 4-year Students



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

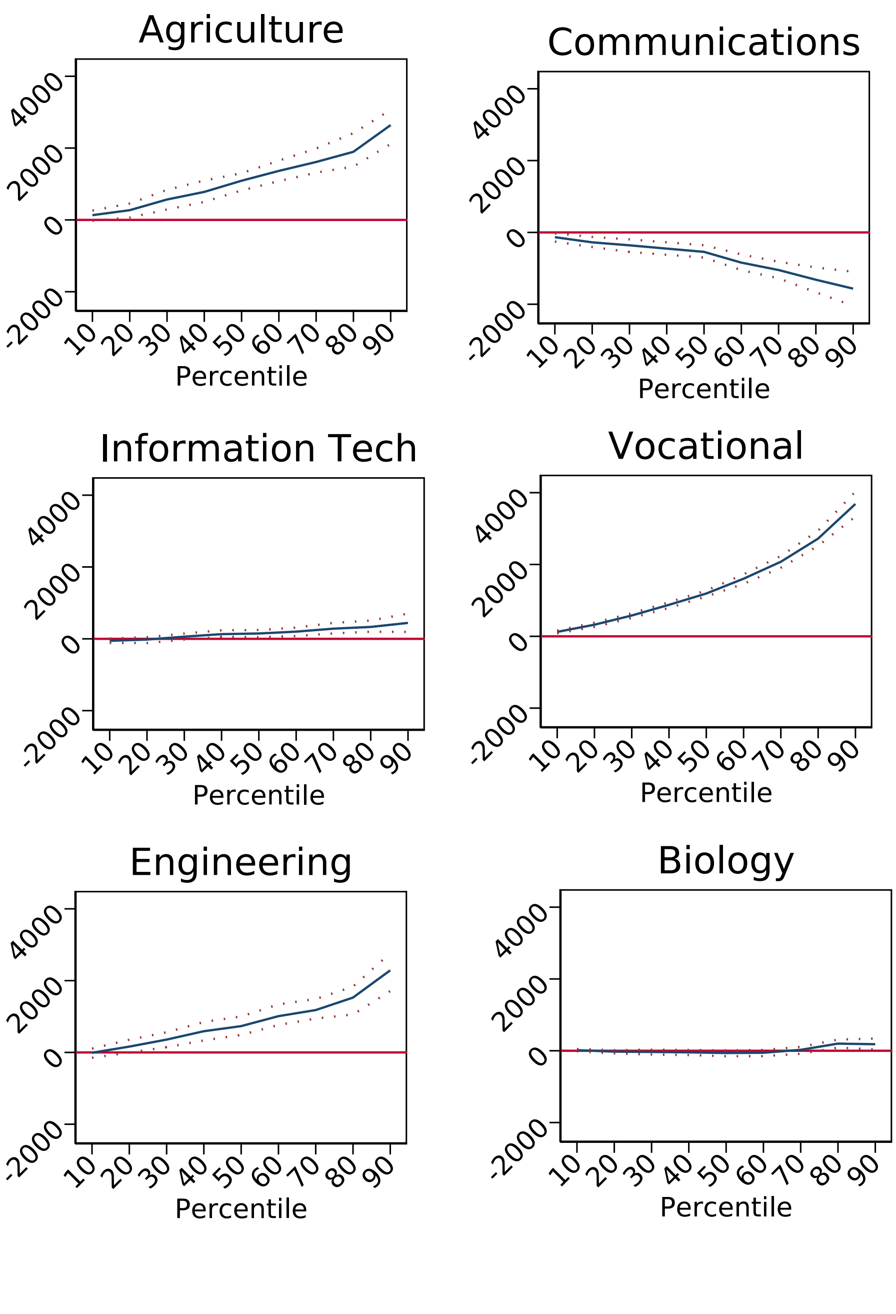
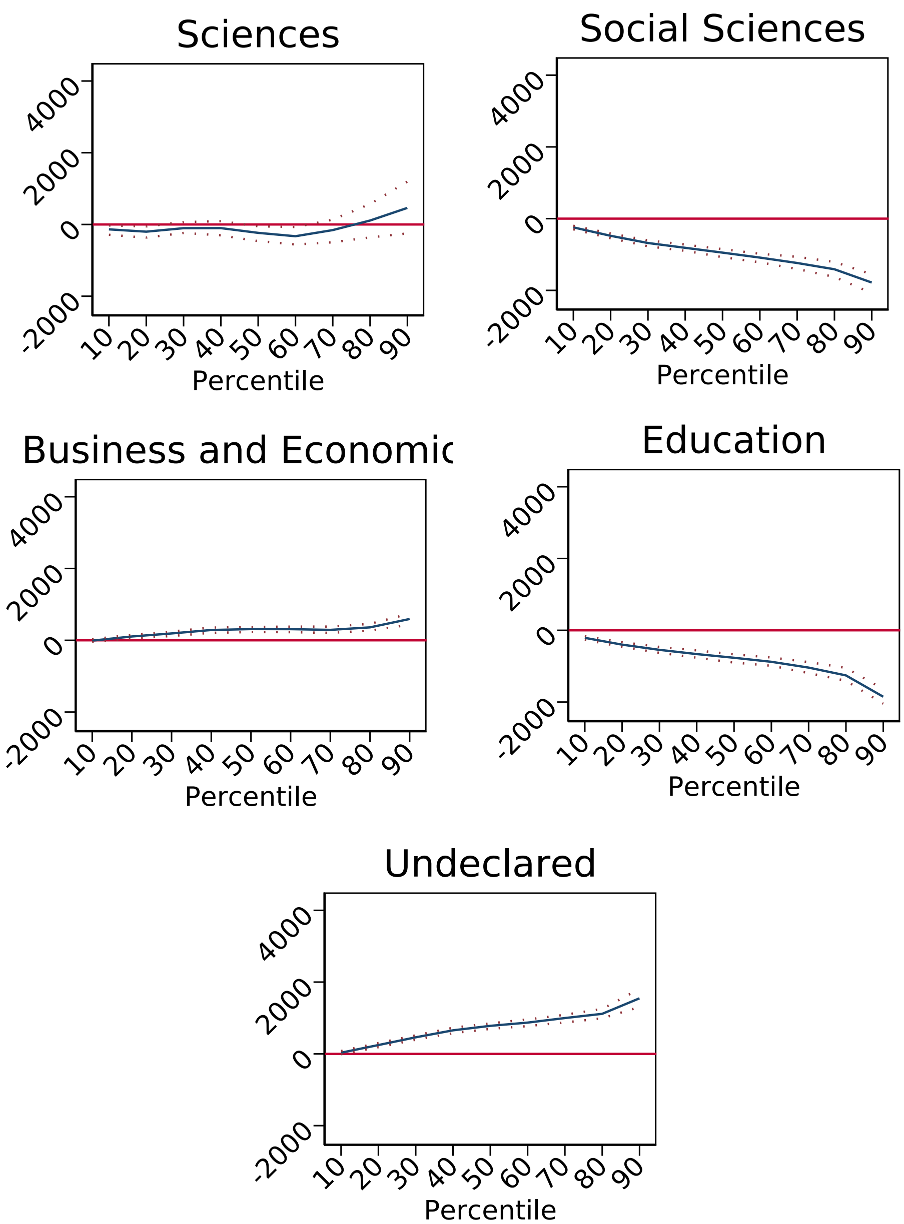


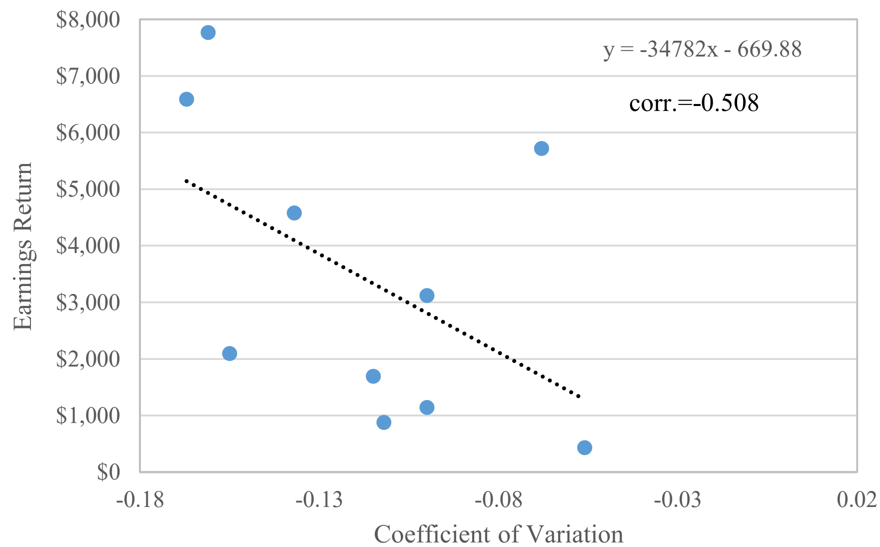
Figure 8 (cont'd): Quantile Treatment Effects of Major on Average Quarterly Earnings - 2-year Students



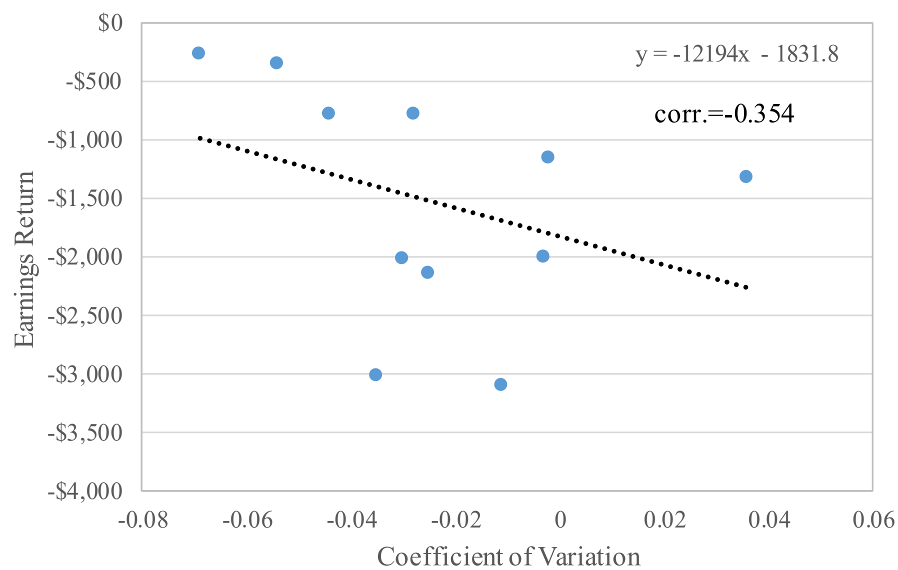
Notes: All estimates are relative to liberal arts majors and include controls for high school test scores, student demographics, HS-by-cohort fixed effects, and college-by-cohort fixed effects. Outcomes are in dollars of quarterly earnings ($2016). The solid curve shows quantile treatment effects for 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 9: 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.

Online Appendix: Not for Publication

Table A-1: Means of Analysis Variables by Major

4-year Students												
Variable	Liberal Arts	Agri-culture	Comm-unications	IT	Voc-ational	Eng. & Arch.	Bio & Health	Science & Math	Social Science	Bus. & Econ.	Educ-ation	Undec-lared
Math Exam Score	0.468	0.604	0.528	0.865	0.388	0.968	0.652	0.968	0.509	0.678		0.346
Reading Exam Score	0.515	0.539	0.608	0.62	0.34	0.678	0.584	0.675	0.570	0.538		0.325
Top Ten Percent Math	0.209	0.246	0.229	0.445	0.181	0.515	0.310	0.509	0.226	0.301		0.205
70th-90th Percentile Math	0.284	0.327	0.300	0.317	0.273	0.301	0.306	0.312	0.296	0.324		0.240
Top Ten Percent Reading	0.278	0.273	0.315	0.347	0.191	0.380	0.317	0.365	0.298	0.277		0.217
70th-90th Percentile Reading	0.292	0.307	0.320	0.315	0.255	0.318	0.304	0.326	0.309	0.301		0.244
Male	0.307	0.622	0.369	0.856	0.630	0.759	0.289	0.557	0.298	0.535		0.537
White	0.668	0.906	0.668	0.642	0.587	0.661	0.551	0.682	0.632	0.656		0.451
Hispanic	0.225	0.064	0.182	0.164	0.239	0.196	0.239	0.206	0.211	0.176		0.282
Black	0.080	0.024	0.111	0.086	0.155	0.053	0.115	0.051	0.114	0.090		0.202
Asian	0.025	0.004	0.037	0.106	0.017	0.088	0.093	0.059	0.040	0.076		0.062
At Risk	0.182	0.130	0.143	0.135	0.228	0.102	0.151	0.107	0.166	0.142		0.277
Economically Disadvantaged	0.163	0.055	0.107	0.148	0.205	0.136	0.192	0.154	0.152	0.131		0.232
Earnings 5-10 Years Post-HS	6,244	7,509	6,722	8,939	7,015	10,750	6,959	7,590	5,941	8,966		6,308
Earnings 10-15 Years Post-HS	10,340	13,566	11,867	16,196	12,582	19,935	13,460	14,365	10,958	15,989		10,546
Earnings 15-20 Years Post-HS	13,032	18,202	15,876	22,112	16,016	26,995	19,299	20,195	14,491	21,982		14,549

2-year Students												
Variable	Liberal Arts	Agri-culture	Comm-unications	IT	Voc-ational	Eng. & Arch.	Bio & Health	Science & Math	Social Science	Bus. & Econ.	Educ-ation	Undec-lared
Math Exam Score	0.087	0.011	0.005	0.091	-0.134	0.353	-0.006	0.519	-0.100	0.065	-0.109	0.136
Reading Exam Score	0.151	0.009	0.255	0.027	-0.178	0.155	0.08	0.344	0.085	0.047	-0.012	0.169
Top Ten Percent Math	0.155	0.151	0.134	0.178	0.163	0.218	0.125	0.271	0.131	0.142	0.118	0.182
70th-90th Percentile Math	0.192	0.172	0.183	0.197	0.139	0.253	0.169	0.291	0.152	0.187	0.144	0.198
Top Ten Percent Reading	0.186	0.172	0.200	0.176	0.172	0.182	0.156	0.228	0.178	0.154	0.147	0.207
70th-90th Percentile Reading	0.205	0.173	0.230	0.180	0.131	0.214	0.186	0.258	0.190	0.181	0.172	0.206
Male	0.461	0.813	0.516	0.762	0.769	0.873	0.245	0.560	0.240	0.470	0.313	0.490
White	0.555	0.880	0.509	0.483	0.481	0.452	0.498	0.526	0.465	0.480	0.471	0.567
Hispanic	0.282	0.089	0.358	0.33	0.393	0.438	0.365	0.368	0.376	0.348	0.412	0.271
Black	0.133	0.029	0.122	0.158	0.113	0.084	0.115	0.074	0.148	0.148	0.109	0.129
Asian	0.027	0.001	0.008	0.026	0.011	0.024	0.021	0.028	0.010	0.021	0.006	0.030
At Risk	0.358	0.362	0.375	0.408	0.480	0.350	0.391	0.272	0.414	0.380	0.415	0.346
Economically Disadvantaged	0.241	0.119	0.258	0.306	0.344	0.332	0.315	0.265	0.326	0.290	0.359	0.211
Earnings 5-10 Years Post-HS	5,468	6,705	4,845	5,640	6,794	6,351	5,618	5,390	4,566	5,871	4,808	6,415
Earnings 10-15 Years Post-HS	8,643	10,128	7,497	8,689	10,128	10,043	8,385	9,812	6,957	8,877	6,902	9,743
Earnings 15-20 Years Post-HS	11,494	12,506	10,256	11,679	12,763	13,631	10,489	13,460	9,331	11,716	8,933	13,022

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-2: Returns to Major Relative to Liberal Arts, by Years Relative to High School - 4-year Students

	4-year Students				2-year Students			
	α		β		α		β	
Field of Study	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agriculture	2404.78	1050.88	22.758	5.135	-104.93	-857.87	6.096	1.230
	(77.58)	(88.79)	(1.435)	(1.525)	(842.90)	(925.51)	(15.307)	(16.832)
Communications	1797.83	1213.57	4.817	-4.088	-867.62	-560.66	-25.877	-22.531
	(51.43)	(52.04)	(0.922)	(0.974)	(139.46)	(153.43)	(2.450)	(2.709)
IT	3453.61	3130.70	48.915	18.922	-363.63	-372.37	-6.966	-13.157
	(112.06)	(113.92)	(2.426)	(2.229)	(194.52)	(199.84)	(3.432)	(3.604)
Vocational	2116.11	2055.29	11.216	4.203	930.81	1101.19	-9.477	-10.069
	(49.40)	(49.34)	(0.878)	(0.884)	(149.61)	(123.17)	(1.560)	(1.409)
Engineering + Architecture	5519.90	4429.65	62.873	28.243	289.79	312.15	-20.293	-29.644
	(119.94)	(105.17)	(1.659)	(1.590)	(332.16)	(350.94)	(10.814)	(11.618)
Biology + Health	1469.61	1096.54	37.141	33.668	210.25	525.24	-14.697	-6.304
	(101.16)	(97.04)	(2.008)	(1.760)	(57.02)	(59.26)	(0.967)	(1.038)
Physical Sciences + Math	2092.01	1298.11	35.761	14.568	-148.44	-197.34	0.141	-6.771
	(229.59)	(233.70)	(4.232)	(4.224)	(189.33)	(194.78)	(3.663)	(3.984)
Social Sciences	938.13	430.19	2.812	-1.116	-1010.29	-514.45	-20.737	-12.915
	(41.08)	(39.67)	(0.820)	(0.812)	(91.71)	(87.05)	(1.652)	(1.530)
Business + Economics	4074.64	3603.46	35.695	21.248	267.09	501.53	-16.016	-13.077
	(59.95)	(56.76)	(1.227)	(1.013)	(71.78)	(72.84)	(1.058)	(1.084)
Education					-944.16	-280.10	-26.801	-16.319
					(74.04)	(80.50)	(1.446)	(1.360)
Undeclared	1007.62	1603.36	7.838	0.118	646.66	604.23	-12.875	-12.514
	(240.64)	(252.83)	(6.951)	(7.421)	(74.12)	(73.58)	(1.376)	(1.434)
Constant	4870.37	4630.26	60.535	46.272	5274.12	3806.54	65.501	52.848
	(36.97)	(220.99)	(0.504)	(4.479)	(38.42)	(284.33)	(0.613)	(5.731)
Controls		x		x		x		x
HS-cohort & College-cohort FE		x		x		x		x
Observations	484,605	483,708	484,605	483,708	154,149	155,802	155,802	154,149
Dep. Var. Mean	6536	6536	76.95	76.95	44.93	44.93	44.93	44.93

Notes: Authors' estimation as described in the text using linked administrative K-12, higher education, and quarterly earnings data from Texas. The β estimates is the slope of earnings with respect to quarters after high school, and the α estimates are the y-intercepts that are calculated using earnings 5 years after high school extrapolated to time 0 using the slope. 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.

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