Investment over the Business Cycle: Insights from College Major Choice*

Erica Blom[†] Brian C. Cadena[‡] Benjamin J. Keys[§]

October 2020

Abstract

How does personal exposure to economic conditions affect individual human capital investment choices? Focusing on bachelor's degree recipients, we find that cohorts exposed to higher unemployment rates during typical schooling years select majors that earn higher wages, have better employment prospects, and lead to work in a related field. Conditional on expected earnings, recessions also encourage women to enter male-dominated fields, and students of both genders pursue more difficult majors. We conclude that economic environments change how students select majors, and we find evidence that students who respond to the business cycle enjoy earnings typical of their new majors.

*We thank Joe Altonji, Lisa Kahn, Ofer Malamud, Thomas Lemieux, Seth Zimmerman, and numerous seminar and conference participants for helpful comments. Min Kim and Richard Jin provided outstanding research assistance. Portions of this paper began as independent work by Blom (superseding relevant sections of Blom 2012 and by Cadena and Keys. First draft: September 2014.

[†]Urban Institute; E-mail: eblom@urban.org

[‡]Department of Economics, University of Colorado-Boulder, and IZA, E-mail: brian.cadena@colorado.edu

[§]The Wharton School, University of Pennsylvania, and NBER, E-mail: benkeys@wharton.upenn.edu

1 Introduction

The consequences of economic fluctuations are large and long-lasting, especially among new labor market entrants such as recent college graduates (Kahn 2010; Oreopoulos, von Wachter, and Heisz 2012). In addition to creating immediate interruptions in employment and income, recessions have recently been shown to have a broad and permanent influence on household decision-making across a variety of domains.[1] Personally experiencing economic downturns affects the formation of subsequent expectations (Malmendier and Nagel 2016), risk preferences (Malmendier and Nagel 2011), and beliefs about the role of luck in success (Giuliano and Spilimbergo 2014).

In this paper, we explore how individuals' personal exposure to economic conditions affects their choice of a specific field of study in post-secondary education. In the face of a depressed labor market, potential students are more likely to continue their education and enroll in post-secondary education (Sakellaris and Spilimbergo 2000; Christian 2007; Long 2015) or graduate school (Bedard and Herman 2008). Recent work, however, suggests that the allocative margin of degree field may be as important as the choice to attend or to complete college at all. For example, Altonji, Blom, and Meghir (2012) show that the variation in earnings across college majors is nearly as large as the average wage gap between college and high school degree holders.

We leverage publicly available data on over 50 cohorts of U.S. college graduates to examine two specific research questions. First, does the business cycle affect the distribution of selected majors among college completers? Second, which characteristics of degree fields predict how a field's share changes with macroeconomic conditions? We begin by outlining a framework for thinking about how students select their major. Conditional on enrollment, students choose to maximize the present discounted value of both future earnings and the non-pecuniary benefits (e.g. prestige or degree of difficulty) of a major. This general framework distinguishes among several sources of utility differences across majors, including permanent characteristics, long-run trends, changes related to the business cycle, and individual-specific preferences and skills. Our analysis of the importance of cyclical changes relies on the assumption that any changes in utility resulting from structural changes in higher education or in the labor market are gradual enough such that they can be well approximated by flexible major-specific trends. In order to draw causal inference, we assume

[1] See, for instance, Ruhm (2000) on health and mortality, Currie and Schwandt (2014) on childbirth, and Hoynes, Miller, and Schaller (2012) on the broader labor market impacts of recessions.

that, conditional on major fixed effects and these major-specific trends, the state of the business cycle when a student is choosing their college major is independent of other changes to the relative utility of college majors.

To answer these research questions empirically, we use more than 4.8 million observations from the American Community Survey (ACS), which, starting in 2009, collects data on field of study for all respondents with a Bachelor's degree. Unlike cohort-specific data sets that capture college major, these new data from the ACS allow us to trace out a detailed distribution of college majors among U.S.-born degree-holders for more than fifty birth cohorts who experienced substantial variation in labor market conditions during the ages when human capital decisions are typically made. This large number of cohorts facilitates the requisite flexible controls for potentially unobservable differences and differential changes in the value of each major. In addition, the large sample sizes from ten waves (2009–2018) of the ACS allow us to estimate major choices at a detailed level of disaggregation. Importantly, we are able to provide estimates separately for men and women, which is essential given their dramatically different trends in college attainment and occupational choice over the last fifty years (Turner and Bowen 1999; Goldin, Katz, and Kuziemko 2006; Goldin and Katz 2009; Gemici and Wiswall 2014).

Figure 1 presents initial evidence that the distribution of college majors in a given cohort is responsive to the business cycle. The solid line in the figure shows the time-series from 1960 to 2013 of expected earnings for men with a Bachelor's degree who turned 20 during the reference year.[2] This variable is calculated as the weighted average of mid-career earnings for men with a given major, using the share of each cohort selecting a given major as weights. Importantly, the expected earnings for a given major are treated as fixed, and the average for a cohort changes *only* through differences in the distribution of completed majors. The dashed line presents the prevailing national unemployment rate in the year that each cohort turned 20 years of age and were most likely choosing their area of study. The figure provides the first piece of evidence that college major choices are responsive to the business cycle, with these two series strongly co-varying (correlation coefficient = +0.60).

This striking figure motivates our subsequent empirical analysis. Using de-trended multinomial logit regressions (or linear approximations thereof), we begin by estimating how choices among 38 college major categories change as the unemployment rate rises. For women, the fields with the largest gains in share are nursing, accounting, and computer-

[2]The average expected earnings range from \$92,000 to \$96,000 in Figure 1 because we focus on the full-time, full-year earnings of mid-career college educated males (ages 35–45), measured in 2010 dollars.

related fields. For men, the largest gains are in engineering, accounting, business, and the natural sciences. In contrast, students of both genders leave fields such as sociology and education-related fields during recessions. Adding up the average marginal effects from a multinomial logit reveals that a one percentage point increase in the unemployment rate leads to a 4.2 percentage point reallocation for women, and a 2.9 percentage point total reallocation of majors for men. These changes occur consistently over time (pre- vs. post-1980), and the responses are quite symmetric over the course of a cyclical rise and fall in the unemployment rate. Scaled to a typical recession-based increase in unemployment of three percentage points, our findings suggest that recessions dramatically affect the skill content and academic specialization of cohorts.

Because the ACS data record college major only for bachelor's degree holders, changes in the distribution of observed completed college majors over the business cycle may occur both by changing the distribution of majors among inframarginal graduates and by altering the composition of the cohort that eventually completes college. Previous studies have found a substantial influence of the business cycle on other margins of human capital investment including college enrollment (Betts and McFarland 1995; Hershbein 2012) and college completion (Dynarski 2008; Kahn 2010), which suggests that there is scope for compositional changes to drive a portion of the changing major distribution.[3] To investigate the role of composition, we introduce controls for changes in the observable characteristics of cohorts, including race/ethnicity and place of birth, which have little effect on our estimates. In addition, we address potential changes in the unobservable characteristics of cohorts by interacting the share of the cohort that enrolls in or completes college with each of our 38 major-specific dummy variables. These interactions allow each major's share to change as the selection process into a college education changes for any reason. These additional results support the conclusion that the observed changes in major shares over the business cycle are largely due to students whose college completion decision was unaffected by the business cycle.

Quantifying how each major's popularity responds to changes in the unemployment rate facilitates our approach to the second research question: What (permanent) characteristics of majors are associated with a net gain or loss in "market share" of students as a result of the business cycle? Because we have cyclicality measures for 38 separate major groupings, we are able to examine this question rigorously. Using detailed data on major-specific charac-

[3]See also Dellas and Sakellaris (2003) and Barr and Turner (2013) on enrollment, and Light and Strayer (2000) and Bound, Lovenheim, and Turner (2010) on college completion.

teristics from the ACS and the 1993 wave of the Baccalaureate and Beyond (B&B) 1993, we investigate a number of specific hypotheses. First, we examine the degree to which students respond to long-run (permanent income or labor force attachment) and/or short-run (e.g. finding a job more quickly) labor market prospects during recessions. Overall, these factors explain the majority of the variation in major reallocation across the business cycle, which suggests that much of the reallocation occurs because students prefer majors with better employment prospects during a recession.

Next, we explore whether students respond to various major-specific attributes beyond labor market prospects, such as difficulty, gender balance, breadth of job opportunities, pathways to graduate school, and subsequent geographic labor mobility. We find that students move into fields with lower average grades, even conditional on earnings potential. A possible explanation is that students facing weak labor markets prefer to send a stronger signal about their ability to a potential employer (Spence 1973). Similarly, women have increasing preferences for male-dominated, more difficult, and more career-oriented majors even *conditional* on long-run earnings potential. The results reveal that recessions not only change the weight students place on earnings prospects, but they also change how students consider other degree field characteristics.

Finally, we examine whether those who complete a different major as a result of the business cycle have earnings typical for the major. We compare the earnings distributions for degree holders who completed a counter-cyclical major in times of high or low unemployment. We find no evidence that graduates in times of high unemployment are more likely to end up in the left tail of the earnings distribution, which suggests that students whose choice of field responds to the business cycle experience the gains in earnings associated with their new major.

This set of results contributes to multiple strands of the literature. First, our analysis of major choices further develops a growing literature on the effects of the business cycle on higher education attainment more generally. This literature initially focused on the extensive margins of whether to enroll and to complete additional years of post-secondary schooling.[4] In addition to the work previously discussed, there is evidence that graduate school attendance increases during recessions (Bedard and Herman 2008; Johnson 2013). Our results are especially complementary with Bedard and Herman (2008) who show that recessions induce STEM majors to attend graduate school. We find an additional adjustment

[4]Interestingly, Charles, Hurst, and Notowidigdo (2018) show that the impact of labor market conditions on educational attainment was especially pronounced during the most recent business cycle.

mechanism whereby students select undergraduate majors that lead directly to jobs, such as engineering or nursing. More generally, we build on this literature by providing evidence that business cycles alter the type of post-secondary education that individuals acquire in addition to affecting the overall quantity of completed schooling. In contrast to previous work that investigated the role of economic conditions on the choice of specific careers, such as engineering (Freeman 1976; Ryoo and Rosen 2004) and investment banking (Oyer 2008), this paper examines the effect of changing demand conditions on the full distribution of human capital content across the entire college-educated labor market. The finding that the distribution of completed majors shifts toward fields that lead to jobs in more recession-proof sectors parallels canonical findings that workers shift toward industries with smaller demand declines during downturns (Davis and Haltiwanger 1990).

Second, our findings expand on a more recent strand of literature that examines major choice in relation to the business cycle. A key example is Beffy, Fougère, and Maurel (2012), who study the role of expected earnings in major choices by comparing two different French cohorts, one of which attended university during a recession and one that attended during a boom. Other recent papers, developed contemporaneously with ours, also explore the effect of either the business cycle or demand conditions more generally on major choice (Bradley 2012; Long, Goldhaber, and Huntington-Klein 2015; Urrutia 2016; Shu 2016; Liu, Sun, and Winters 2019; Weinstein 2020; Ersoy 2020). Relative to these studies, our paper is distinct because its empirical approach requires and relies on more business cycles (1960–2013), which allows us to identify cyclical responses even in the presence of other long-run trends in the desirability of majors. Other studies using a single cycle typically must assume that unobservable factors affecting the net utility of a major are stable over time. Further, our use of the ACS and its large underlying samples allows us to examine the cyclical responses of more than 30 detailed major categories separately by gender. Having characterized cyclical responses among a large number of categories, we are able to investigate systematically the pecuniary and non-pecuniary factors (difficulty, math intensity, gender typicality) that drive cyclical major growth. This type of analysis represents, to our knowledge, a wholly new approach in this literature.

Third, our results extend the broader literature examining the determinants of major choice. Prior research has creatively explored how students form expectations about a particular major's career and earnings prospects, and how these expectations affect students' choices (Betts 1996; Montmarquette, Cannings, and Mahseredjian 2002; Arcidiacono 2004; Zafar 2011; Arcidiacono, Hotz, and Kang 2012; Beffy, Fougère, and Maurel 2012; Zafar 2013;

Wiswall and Zafar 2015a,b).[5] While these papers typically find that students place at least some weight on expected earnings when making major choices, our results suggest that students value earnings prospects even more during recessions. This literature also suggests that information is a likely mechanism behind our results, as multiple studies find that students know relatively little about differences across fields in expected earnings, and that providing information about these earnings prospects can influence students' choices (Arcidiacono, Hotz, and Kang 2012; Hastings, Neilson, and Zimmerman 2015; Wiswall and Zafar 2015a,b; Baker et al. 2018; Conlon 2019). Our results are therefore consistent with the interpretation that the recessionary environment induces students to acquire more information than they would under stronger demand conditions.

Fourth, the result in this paper that women are especially responsive to changes in economic conditions and that this differential responsiveness may reduce the gender gap in affected cohorts contributes to the literature on the gender gap in major choices (Killingsworth and Heckman 1986; Brown and Corcoran 1997; Turner and Bowen 1999; Blau and Kahn 2007; Gemici and Wiswall 2014). Our finding is consistent with previous research showing that women typically weight non-pecuniary factors more heavily (Wiswall and Zafar 2015a), which may give them more scope for adjustment as the business cycle changes. Relatedly, we contribute to the literature on the determinants of STEM majors (Ehrenberg 2010; Arcidiacono, Aucejo, and Hotz 2016; Card and Payne 2017). A rise in the unemployment rate encourages more students, especially women, to pursue STEM majors. This fact suggests room for other interventions during college, although further research would be needed to identify the optimal design.

Finally, our results add a new dimension to the literature showing that students who graduate in a recession suffer from the timing of their exit from school (see, e.g. Oyer 2006, Kahn 2010, and Wee 2013). Students leaving fields that are most hurt during recessions and entering recession-proof fields such as engineering and nursing partially offsets the costs of graduating in a recession.[6] We use our main results to calculate that the offsetting labor supply response along this intensive margin is roughly one-tenth of the labor demand effect

[5] Addditional related work considers the role of students' beliefs about their ability (Stinebrickner and Stinebrickner 2014). Recent work in Chile (Hastings, Neilson, and Zimmerman 2014) and in Norway (Kirkebøn, Leuven, and Mogstad 2016) has exploited discontinuities in centralized admissions processes to show that much of the observed difference in earnings by major represent the causal effect of a student's chosen field of study.

[6] Note that the "extensive margin" compensating behaviors of increased attendance and completion of college during recessions increase the supply of college graduates competing for post-graduation employment, which likely exacerbates the negative impact of graduating in a recession (Hershbein 2012; Johnson 2013).

of graduating in a recession.

The remainder of the paper is organized as follows: Section 2 provides a conceptual framework of the college major decision to motivate our primary empirical specification; Section 3 describes the data and identifies cyclical changes in the distribution of completed majors; Section 4 examines the role of pecuniary and non-pecuniary factors in driving majors' cyclicality; Section 5 concludes.

2 Conceptual Framework and Empirical Specification

In this section we present a stylized framework that motivates the empirical approach to our first research question: How does the business cycle affect the share of cohorts selecting each major? We abstract from the choice to enroll in college and instead focus solely on the choice of college major conditional on enrollment.[7]

We begin by defining the utility of major m for student i in cohort c to be U_{icm}. In a life-cycle context, as in Altonji (1993), Arcidiacono (2004), and Altonji, Blom, and Meghir (2012), this utility captures both the major's present discounted value of future earnings (which operates through the set of possible career paths) and any non-pecuniary benefits.[8]

Suppose we can decompose U_{icm} into fixed, structural, cyclical (which may be major-specific), and individual components as follows:

$$U_{icm} = \eta_m + \mu_{cm} + \gamma_{cm} + \epsilon_{icm} \tag{1}$$

The fixed component of the utility "return" to a major, η_m captures all of the fixed (across cohorts) components of the major's potential employment and wage opportunities, as well as non-pecuniary costs and benefits, over the life-cycle. For example, a degree in Engineering has always required more math-intensive coursework and has always led to a more specific set of career options as compared to a degree in Sociology. Over the time period of our study (cohorts turning 20 from 1960-2013), a number of "structural" (μ_{cm}) factors have also altered the relative utility of different majors. For example, in more recent

[7] This approach effectively treats the major choice decision as deriving from a nested logit. The empirical results would therefore be unaffected by the addition of another "major" category for completed education less than a Bachelor's degree.

[8] Previous research has often used assumptions regarding rational expectations (see, e.g. Berger 1988), or myopic expectations (as in Freeman 1976) about the path of future wages, which depend on both the actual degree of wage persistence as well as the degree of information constraints facing students. See Zafar (2011) and Arcidiacono, Hotz, and Kang (2012) on how college students actually form these expectations.

cohorts, women have faced fewer barriers to completing traditionally "male" majors and to working in occupations fed by these majors, which increases the relative utility of pursuing those types of degrees.

Note that without further assumptions, it is not possible to separately identify the influence of structural changes versus cyclical changes because both operate at the cohort $\times$ major level. In what follows, our key assumption is that any changes in utility resulting from these types of structural components occur gradually over time, and thus can be represented by a major-specific, sufficiently smooth, function of time (birth cohort), $\mu_{cm} = f_m(c)$. In other words, any long-run structural characteristics of a major must change gradually rather than systematically rising and falling with the higher frequency variation in demand conditions over a business cycle.

The use of multiple business cycles helps to support this assumption, as long as potential changes to a particular major's relative utility are not correlated with the rise and fall of *every* business cycle. Empirically, we operationalize this assumption by including both major fixed effects and flexible major-specific trends to account for unobservable characteristics of majors that are either permanent or smoothly time-varying. Including these controls in specifications run separately for men and women allows us to remove the influence of substantial differences in long-run trends for men and women over this time period (Gemici and Wiswall 2014).

The cyclical component, γ_{cm}, reflects the fact that each major fares differently over the business cycle, which can occur for multiple reasons. First, the business cycle likely changes students' incentives to gather information about the relative labor market prospects offered by each major, with recessions leading students to investigate the differential prospects in more depth. Relatedly, a slack labor market may induce students to approach their major decision from more of an "investment" rather than a"consumption" perspective. Further, job market prospects change differentially across business cycles, with higher-earning majors tending to see smaller declines in earnings and employment rates (Oreopoulos, von Wachter, and Heisz 2012), and students may rationally be drawn to these majors during times of greater labor market risk. A weaker expected job market at graduation could also lead to an arms race for credentials, with students choosing more difficult majors to signal their quality, even if their intended career paths are unchanged. In addition, students may choose an alternative major with the explicit goal of increasing their likelihood of graduation, which could lead them to pursue less demanding fields of study.[9]

[9]Although we treat the student as the primary actor in discussing each of these mechanisms, in many

Our initial empirical aim is to determine the combined effect of all of these (and any other) factors. We begin by simply asking whether the unemployment rate has any effect on the distribution of completed majors. This approach allows us to estimate the effect of the unemployment rate semi-parametrically rather than as a function of major characteristics. To do so, we allow for the utility of each major to depend on the unemployment rate by allowing for major-specific coefficients on the unemployment rate: $\beta_m * unemp_c$.[10] After determining how each major fares over the business cycle, we then examine how these responses are related to majors' characteristics, to help determine which of the above factors are most important in driving cyclical changes.

Re-writing Equation (1) to include these assumptions provides the initial basis for a functional form:

$$U_{icm} = \beta_m * unemp_c + \eta_m + f_m(c) + \epsilon_{icm} \tag{2}$$

The student chooses major m^* such that $U_{icm^*} \geq U_{icm}\ \forall m \neq m^*$.[11] Because the unemployment rate is a cohort-level characteristic, in our main specifications we aggregate to cohort-major cells and run regressions based on the functional form suggested by this model. To reach our main empirical specification, consider how the observed population shares in a given cohort-major (S_{cm}) will depend on the cohort's true choice probability ($Pr(m = m^*) \equiv \pi_{cm}$) plus sampling error:

$$S_{cm} = \pi_{cm} + \nu_{cm} \tag{3}$$

Assuming ϵ_{icm} is independent across majors and has a Type I extreme value distribution, we can expand the above equation to:

$$S_{cm} = \frac{e^{\beta_m * unemp_c + \eta_m + f_m(c)}}{\sum_M e^{\beta_m * unemp_c + \eta_m + f_m(c)}} + \nu_{cm} \tag{4}$$

The denominator of the π_{cm} portion is a constant (within cohort), so for simplicity we

cases students are likely influenced by their parents who may encourage their children to pursue certain majors for similar reasons.

[10] In the main analysis, we use the national unemployment rate. Appendix Section A-10 demonstrates that the results are qualitatively similar when using the unemployment rate for each individual's state of birth. Results using only local variation in cyclical changes are less precisely estimated, and we discuss these results in more detail in section 4.3.3.

[11] The assumption that students choose the highest utility major implicitly assumes that institutions can accommodate the increased demand. We find this assumption to be reasonable for the relatively modest changes in shares that occur over the business cycle, and we note that a failure of this assumption would likely bias the results toward zero.

denote it as $e^{-\gamma_c}$:

$$Pr(m = m^*) = e^{\beta_m * unemp_c + \eta_m + f_m(c) + \gamma_c} + \nu_{cm} \tag{5}$$

Taking logs and linearizing around $\nu_{cm} = 0$ yields:

$$log(S_{cm}) \approx \beta_m * unemp_c + \eta_m + f_m(c) + \gamma_c + \frac{\nu_{cm}}{\pi_{cm}} \tag{6}$$

Empirically, we approximate structural changes in majors with a major-specific quadratic time trend, $f_m(c) = \delta_{1m}c + \delta_{2m}c^2$, which combined with the major fixed effects allows for a rich set of unobservables to affect majors' relative shares in each cohort. In addition, we bootstrap the standard errors to account for heteroskedasticity (due to the influence of π) and the non-independence of the error terms within cohort. The long time dimension of our panel supports this method of conducting inference, which is important because the cohort level is the effective level of variation.

A semi-elasticity regression specification such as this one faces the challenge that we cannot separately identify a cohort-specific fixed effect, γ_c, and all of the β_m coefficients on $unemp_c$. We address this issue by assuming that the cohort-specific fixed effects are zero for all cohorts. In effect, this assumption implies that the average log(share) of majors for a cohort is unrelated to the unemployment rate. Briefly, this assumption allows us to avoid choosing a reference major to compare our results to, and it keeps our specification more easily interpretable than a multinomial logit specification, which would directly impose an adding up constraint.[12] Appendix Figure A-1 provides a direct comparison of the average marginal effects from a multinomial logit specification and our semi-elasticity approach, showing similar results both qualitatively and quantitatively. We also include specifications with the share (not logged) as the dependent variable. In these specifications, this assumption holds by construction as the average share is $\frac{1}{M}$ in every year.

Finally, a note on causality. In order to draw causal inference, we must assume that, conditional on the major fixed effects and major-specific quadratic trends, the state of the business cycle when a student is choosing her college major is independent of other changes to the relative utility of college majors. Given that reverse causality is infeasible (students' choices of college major do not determine the national unemployment rate), and that overall trends in major shares appear to be fairly smooth, we believe this to be a reasonable

[12] Directly imposing an adding up constraint would be more computationally intensive, which is the key drawback. In addition, our primary approach is more transparent about the effective level of variation (cohort) compared to individual-level specifications.

assumption. Remaining threats to identification would need to take the following form: the relative value of majors change consistently with the business cycle for reasons other than the business cycle itself. An example would be a policy designed to encourage students to pursue STEM majors that was systematically counter-cyclical, with more generosity during times of higher unemployment.

3 Cyclical Changes in Major Choices

Our empirical analysis takes advantage of field-of-study questions available beginning in the 2009 wave of the American Community Survey.[13] In this roughly one percent per year cross-sectional sample of the U.S., all respondents with a bachelor's degree or higher were asked to report the field of study for their bachelor's degree. We calculate the distribution of college majors for U.S.-born individuals turning age 20 from 1960–2013, using more than 4.8 million individual records found in the 2009–2018 ACS.[14] We aggregate the fields of study into 38 categories in order to facilitate the analysis in the following section that includes characteristics as measured in the Baccalaureate and Beyond dataset.[15] The ACS also includes the respondent's age, which allows us to add age-specific national unemployment rates to each record.[16]. We use this data source to determine whether and how major choices change over the business cycle.

3.1 Specification and Identifying Variation

We first explore whether there is a systematic relationship between the prevailing unemployment rate when a birth cohort reaches age 20 and the distribution of college majors selected among that cohort's college graduates. In the results below, we estimate a linear regression

[13]We accessed the ACS through the IPUMS web server (Ruggles et al. 2020).

[14]We selected cohorts where we can observe undergraduate degree completion by age 25 in at least one survey year.

[15]We created this list of majors by hand, with the goal of making the aggregate major categories as coherent as possible between the two surveys. Appendix Table A-1 provides more detail on the construction of the 38 major categories used in the analysis.

[16]We use the annual national unemployment rate, calculated among all persons ages 16 and over: BLS series ID LNU04000000 (Bureau of Labor Statistics 2020)

model with major (m) $\times$ birth cohort (c) cells as observations:[17]

$$y_{cm} = \beta_m * \text{unemp\_20}_c + \eta_m + \delta_{1m} * c + \delta_{2m} * c^2 + \epsilon_{cm} \tag{7}$$

We use the 38 major classifications discussed previously and the 54 birth cohorts that turned 20 years old in the years 1960–2013. All of the analysis is run separately for men and women.

In our primary specification, we estimate Equation (7) using the natural log of the major's share within each cohort as the dependent variable. Note that this specification contains a coefficient on the unemployment rate for each major, β_m, controlling for major-specific fixed effects (η_m) and major-specific quadratic time trends. We report standard errors based on a block-bootstrap procedure that resamples entire cohorts, which matches the effective level of variation in the unemployment rate.[18] This block-bootstrapping procedure also allows us to properly account for the fact that the β_m coefficients are estimated with error when we examine how they are related to characteristics of majors.

The specification thus leverages cyclical deviations in major share relative to long-run trends. This approach requires an exceptionally long panel of college majors, which the ACS uniquely provides, in order to flexibly estimate major-specific time trends. In the main text, we rely on major-specific quadratic time trends, while Appendix Section A-2 establishes the robustness of this choice to a variety of parametric and nonparametric alternatives.

Figure 2, which corresponds to the analysis for women, provides examples of the identifying variation isolated by this approach. Panels A and B show both the raw log(share) data (the solid line) and the fitted quadratic time trends (the dashed line) from 1960–2013 for Engineering and for Early and Elementary Education majors, respectively. As each of these fields experienced substantial changes in share over this time period, the importance of controlling for long-run trends is readily apparent in the figure.[19]

The solid lines in Panels C and D of the figure show the residual changes in log(share) after removing the influence of these major-specific time trends. The dashed lines represent a

[17] Nevertheless, we have estimated the corresponding multinomial logit model for robustness, and we include a comparison of the resulting estimates in Appendix Figure A-1. In practice, the choice of methodology has little influence on the substantive conclusions, as the average marginal effects from the multinomial logit are very similar to the linear regression estimates.

[18] We use 5,000 bootstrap trials, and the results of this procedure yield qualitatively similar standard errors compared to using robust standard errors clustered at the cohort level.

[19] Appendix Section A-2 also provides trend analysis for additional example majors that underwent considerable changes (Pharmacy and Computer Science), demonstrating that the quadratic time trends fit quite well even for those fields.

similarly de-trended version of the unemployment rate.[20] The figure shows that the share of women choosing these two types of majors responds quite differently over the business cycle. The share choosing Engineering is strongly countercyclical while the share choosing Early and Elementary Education is strongly pro-cyclical. The estimated coefficients are +0.14 for Engineering and -0.067 for Early and Elementary Education, which implies that each percentage point increase in the unemployment rate increases the share of women choosing Engineering by roughly fourteen percent and decreases the share of women choosing Early and Elementary Education by seven percent.[21]

3.2 Major Cyclicality Results

Figures 3 and 4 provide analogous coefficient estimates of the cyclicality of each of the 38 major categories for each gender. In general, more difficult majors associated with higher salaries tend to gain share while easier majors associated with lower salaries tend to lose share in response to an increase in the unemployment rate. This pattern of changes in completed degrees suggests that recessions induce students to act as if higher-earning majors have higher utility during a recession.[22] There is also a substantial overall shift in the distribution of major choices over the business cycle: among women (men) 25 (18) of the 38 majors have an unemployment gradient that is statistically significant at the 0.01 level, and an additional four (six) majors have coefficients that are different from zero at the 0.05 level. Appendix Table A-3 contains a complete set of numerical results, including standard errors for the coefficient estimates and the long-run average shares for each major separately by gender.

Note that these coefficient estimates are semi-elasticities, and thus that some of the larger percentage changes are due in part to small baseline probabilities. Figures 5 and 6 provide corresponding coefficient estimates of Equation (7) using the raw share values as the dependent variable. This alternative specification shows that, in raw probability terms, the greatest gain among women occurs in Business fields: A one percentage point increase in the unemployment rate leads to a 0.6 percentage point increase in the share of women graduates with business degrees. Similarly, a one percentage point increase in the unemployment rate

[20]Specifically, this line shows the residuals from a regression of the unemployment rate on a quadratic trend fit over the same time period. The corresponding figure for men is provided in Appendix Figure A-2.

[21]Interestingly, Nagler, Piopiunik, and West (2017) find that teachers hired during recessions are higher quality compared to teachers hired at other times. Together, these results imply that recessions lead to a buyer's market for teachers, and college students respond by choosing alternative majors.

[22]It is certainly possible that some students choose less difficult majors in order to increase their likelihood of graduation, but the observed shifts in fields of study among completed degrees imply that the shift toward higher-earning degrees is quantitatively more important.

decreases the share of women with any Education degree by more than one percentage point (combining the coefficients on the two Education fields).

Both figures show that the responses by gender are similar, with most majors either gaining or losing share consistently across both gender groups.[23] Adding up the absolute value of the coefficients for shares yields 4.2 percentage points in total reallocation among women and 2.9 percentage points among men.[24] The stronger response among women along this margin is consistent with women having more elastic labor supply generally (Killingsworth and Heckman 1986; Heckman 1993; Blau and Kahn 2007) as well as with women responding more strongly on other margins to cyclical fluctuations specifically (Bedard and Herman 2008; Johnson 2013; Giuliano and Spilimbergo 2014). Also, given that in the cross-section women appear to have weaker preferences for earnings potential (Zafar 2013), there may be additional room for cyclical growth in high earning majors among women.

As suggested by the similar responses across multiple cycles shown in Figure 2 above, these results are not driven by one particular business cycle. Appendix Section A-5 provides analysis separately for the pre-1980 and post-1980 portions of our analysis, revealing qualitatively similar results in both periods. Further, the responses are relatively symmetric within cycles, with the majors that gain share as unemployment rises experiencing a similarly-sized decline in share during booms. Appendix Section A-6 provides results from an interaction model showing that, for nearly all majors, the responses are similar in magnitude and not statistically significantly different when comparing periods of rising and falling unemployment. Overall, the evidence from this analysis suggests that the business cycle has a substantial impact on the distribution of college majors, with a notable shift toward degrees that tend to pay higher salaries as the labor market softens.[25]

[23]Appendix Table A-4 shows the difference in coefficients, including tests of the differences in elasticities between genders. Although the point estimates differ in sign for a few majors, there is no major where the effects are statistically significantly opposite-signed.

[24]The level of these estimated net reallocation effects is naturally sensitive to the number of major categories. Narrower classifications of major categories would naturally increase these estimates as long as there is some switching happening within these relatively broad categories. Our 38 major groupings combine fields in some cases, and thus do not allow for a switch from majoring in English to majoring in a foreign language to be classified as a reallocation, for example.

[25]In fact, the reallocation toward STEM fields associated with a typical recession is comparable in magnitude to the effects of a program that paid up to $8,000 in cash incentives to students who chose these majors (Denning and Turley 2017).

4 Correlates of Majors' Cyclicality

This section addresses our second research question: What characteristics of majors attract more students in a recession? We explore this question using major attributes as measured in the ACS and in the public use version of the 1993 Baccalaureate and Beyond survey (B&B).[26] Our analysis is limited to the 32 major categories that are identifiable in both data sources.[27] Note that this set of specifications relates each major's measured cyclicality to a set of its characteristics, and we in effect treat the relative differences in characteristics as fixed over time. Although this assumption does not need to be strictly true, the analysis will be most informative if the relative rank ordering of majors does not change substantially over our period of analysis.[28] We divide the set of available major characteristics into four groups: long run labor market characteristics, short run labor market characteristics, degree of difficulty, and other attributes.[29] This division is useful for exploring a range of hypotheses surrounding why certain college majors exhibit greater cyclicality than others.

To do so, we use the semi-elasticity coefficients on the unemployment rate from Equation (7) as the dependent variable and a number of major characteristics as explanatory variables:

$$\hat{\beta}_m = X_m \Gamma + \omega_m \tag{8}$$

Because the dependent variable in this second-stage regression is generated from the earlier "first-stage" analysis, we do not estimate Equation (8) by OLS. Instead we make two adjustments. First, we weight each observation by the inverse of the estimated variance of the β_m term, which we calculate using the bootstrap trial estimates of the β_m's from the first stage.[30] Second, in order to conduct inference, we empirically approximate the sampling distribution of the second-stage coefficients (ϕ's) by repeatedly estimating Equation (8) using

[26] We accessed these statistics using the PowerStats portal, which is accessible via http://nces.ed.gov/datalab/. We created a customized version of the MAJCODE1 variable.

[27] Excluded majors are Actuarial Science; Journalism; Pre-Law/Legal Studies; Pharmacy; Physics; and Public Affairs, Health, Policy.

[28] Changes in these characteristics over time effectively introduce measurement error in the explanatory variables, likely leading to some attenuation bias. In support of this approach, Appendix Section A-5 demonstrates that the major cyclicality results are relatively consistent over time.

[29] Summary statistics for each of these variables is available in Appendix Table A-9.

[30] One key source of heteroskedasticity is that the major-gender cells are differently sized, on average. Estimates of percentage changes in share for smaller majors are substantially more variable, and this weighting ensures that small majors do not exert undue influence on these estimates. In practice, the choice to weight has relatively little impact on the coefficients, although the coefficient estimates are more stable across specifications that include different numbers of major categories (for example, due to data not being available from B&B).

the sets of β_m from the bootstrap trials of Equation (7). The reported standard errors are the standard deviation of the ϕ coefficient from this bootstrapped distribution.

4.1 Major Cyclicality and Labor Market Prospects

We first analyze the relationship between cyclical changes in share and the long-run earnings prospects of a major. Figure 7 presents the relationship between the degree of major cyclicality for women (as estimated above) and median wages of prime-age workers. Each dot represents a major, and the fitted line provides the predicted values from Equation 8. The figure shows a strong positive relationship between average "long-run" wages and the fields that are most responsive to the business cycle, with more female students entering higher-paying fields (such as Engineering and Economics) when unemployment rises. Recall that the cyclicality measures are within-major changes in market share due to higher unemployment, conditional on slow-changing trends. Thus, the results in Figure 7 imply that students behave as though the utility of selecting a major with higher long-run earnings increases during a recession.

The corresponding slope coefficient from Figure 7 is presented in the first column of Table 1. This statistically significant coefficient implies that each ten percent increase in a major's long-run median wages is associated with a 1.5 log point more positive semi-elasticity with respect the unemployment rate. For example, median earnings for Nursing majors are 40 log points higher than for Early Education majors. Majors whose graduates earn in the range of Nursing are expected to see gains in share of roughly 2.9 percent with each one percentage point increase in the unemployment rate. In contrast, majors that pay like Early Education are expected to lose 2.9 percent share with each percentage point rise in unemployment.

Table 1 presents multivariate regressions relating major cyclicality to labor market prospects for women (columns 1–3) and men (columns 4–6), respectively. Beginning in column 1, it is clear that long-run earnings are quite predictive of cyclical changes in share among women. We then add additional controls for the short-term labor market prospects associated with each major. Recall that these are intended to be "typical" short-run characteristics of majors, calculated from a single cross-section, and the coefficients on these variables therefore reflect a changing prioritization of these characteristics rather than a response to cyclical changes in the characteristics themselves. The ability to find employment quickly, and to find related employment in particular, are strong independent predictors of cyclical changes in share conditional on median wages (columns 2 and 3). These explanatory variables are quite correlated with each other, and we therefore avoid interpreting individual coefficients. Instead, we note that these four measures of labor market prospects together explain roughly two-thirds of the overall variation in majors' cyclicality. Columns 4–6 reveal qualitatively similar results for men.[31] Columns 4–6 reveal qualitatively similar results for men.

As discussed in Section 2, there are multiple potential explanations for this observed shift in the major distribution toward those with better earnings prospects. Students may rationally choose majors less affected by a recession (Oreopoulos, von Wachter, and Heisz 2012; Altonji, Kahn, and Speer 2016), and the state of the business cycle can change their information-gathering behavior.[32] Additionally, a recession, along with potential parental encouragement, may lead students to approach their post-secondary studies from an investment rather than a consumption perspective.

Taken together, these results reveal that, despite the fact that most recessions are relatively short-lived, students of both genders make *permanent* investments in fields of study with more favorable long-run labor market potential when the macroeconomy is relatively weak. We further find that both men and women choose majors that have higher employment rates and related employment opportunities one year after graduation. Thus, recessions increase the importance that students place on both being able to find relevant employment soon after graduation and on long-run labor market prospects.

4.2 Major Cyclicality and Broader Major Characteristics

In the standard rational life-cycle model of college major choice (as in Berger 1988), students' major decisions should respond exclusively to long-run earnings prospects. Even if students responded only to changes in expected earnings, the average of other characteristics of their chosen majors would change over the business cycle because majors with better prospects are more difficult, require more math, and are more male dominated, among other features. To summarize these shifts, Appendix Table A-10 provides estimates of unconditional relationships between a major's cyclicality and multiple major attributes.

There is, however, scope for recessions to alter students' choices beyond the effects of a widening gap in expected earnings. In particular, students may experience an incentive to increase their information gathering from typically low levels and to pay closer attention to

[31]In results not reported, we have also considered the variance of earnings among a major as an additional covariate. This additional measure of risk has no additional explanatory power beyond the measures we include.

[32]For direct evidence that higher quality information about earnings affects students' major choices, see Hastings, Neilson, and Zimmerman (2015) and Conlon (2019).

the differences in career prospects afforded by different majors. Additionally, when students anticipate that the post-graduation job market will feature many qualified applicants for the same position, they may choose a more difficult major to signal their quality, even if the new major does not directly affect their productivity (Spence 1973).

In Table 2, therefore, we test whether other major characteristics are related to the cyclicality of college majors, *conditional* on the four variables shown in Table 1. We examine career concerns, measures of major difficulty, and other non-pecuniary features of the major. The results reveal that other major attributes beyond labor market prospects contribute substantially to students' choices.[33]

First, recessions lead more students to choose majors that are effectively "terminal" because they have a higher likelihood of leading to a career without additional schooling. This perhaps surprising result implies that, although some students "wait out" recessions by attending graduate school (Bedard and Herman 2008; Johnson 2013), this behavior likely does not reflect a forward-looking choice of an undergraduate major that more often leads to graduate school. We also find evidence that students move into majors with less concentrated occupation options (based on a Herfindahl–Hirschman Index), and thus more general sets of skills.[34] In addition, majors with a career orientation, i.e. ones with a greater likelihood of working full-time during prime earnings years, gain share as the unemployment rises.

Graduates also choose majors with lower GPAs during recessions, although conditional on changes in labor market prospects, they choose majors that require less math.[35] We also find that, even conditional on long-run earnings, recessions induce students of both genders to choose more male-dominated fields. Finally, recessions lead students to prefer majors associated with a greater likelihood of remaining in their state of birth (statistically significant for women only). Because each of these specifications include the covariates from column (3) of Table 1, these results are not driven by the fact that majors with higher earnings also happen to be male-dominated, more difficult, more career-oriented, or less likely to require a long-distance move. Rather, these results demonstrate that students have

[33]For most of these factors, the conditional coefficients are the same sign but smaller in magnitude than the corresponding coefficients in Appendix Table A-10. Notably, the coefficients for math content switch signs, however, with students preferring more math-intensive majors unconditionally but less math-intensive conditional on changes in expected earnings.

[34]This potentially counter-intuitive result is driven, at least for women, by movements out of Early and Elementary Education, the second most concentrated major (after Pharmacy).

[35]This result does not rule out the possibility that recessions may encourage some students to select less demanding (higher GPA) majors in order to increase their chances of graduating. It does, however, suggest that such an effect is overwhelmed by students choosing more rigorous majors as the unemployment rate rises.

increasing preferences for each of these features independent of their increasing preference for majors with greater long-run earnings potential.

The fact that women in particular are more likely to choose gender-atypical majors and majors with lower average grades during a recession has important implications for policymakers seeking to alter women's participation in these fields. First, these results are consistent with earlier findings that there is a sizable share of women whose academic preparation and ability allow them to complete either a more quantitative major or a more gender-atypical major (Turner and Bowen 1999; Goldin 2013). Additionally, the fact that women are more likely to choose these majors in a recession provides some insight into what types of policy interventions may prove effective in encouraging women to pursue male-dominated fields.[36] Perhaps better information about the relative career prospects or programs designed to encourage women to think of college as an "investment" rather than as "consumption" may be particularly effective. Although we are unable to disentangle the potential mechanisms, it is clear that some aspect of the high unemployment environment effectively encourages women to enter gender-atypical fields. Importantly, this type of exogenous increase in female representation in male-dominated fields may have spillover encouragement effects on subsequent cohorts depending on the nature of the barriers women face in entering those fields (Goldin 2015).

4.3 Robustness

4.3.1 Composition of cohorts

A remaining interpretation question is whether the cyclicality of the distribution of college majors reflects changes in selected fields of study among a stable population or whether a portion of the change results from cyclical changes in the composition of cohorts. There is a substantial literature demonstrating that college entrance and persistence are countercyclical (Betts and McFarland 1995; Dellas and Sakellaris 2003; Barr and Turner 2013). If individuals who are induced to complete a college degree by the state of the business cycle have different preferences than inframarginal students, the observed distribution of completed majors will change, even if inframarginal students' choices are unaffected. In order to separate these influences, we provide additional analysis that adjusts for the composition of observable and

[36] There is some evidence that women's preferences over job characteristics differ from men's (Lordan and Pischke 2016), while several papers suggest that a primary barrier to entry is the more competitive environment found in typically male fields (Gneezy, Niederle, and Rustichini 2003; Niederle and Vesterlund 2007; Buser, Niederle, and Oosterbeek 2014).

unobservable characteristics of cohorts.

One means of addressing this question is to control for the observable characteristics of individuals completing their degrees. In Appendix Table A-11, we compare the main results presented earlier to results that adjust for racial/ethnic composition and place of birth. Because the ACS data is collected well after individuals have completed their schooling, there are relatively few observed characteristics that predate an individual's schooling. We cannot, for example, adjust for a cohort's parental education or income levels, which could affect a cohort's chosen set of majors. Nevertheless, we can control for permanent characteristics that may be correlated with these and other factors that affect field of degree choices. Specifically, we run specifications that augment Equation (7) with race $\times$ major fixed effects, with birth region $\times$ major fixed effects, or with both sets together. These controls therefore allow for the possibility that cohorts observed at different points in the business cycle have different racial compositions and that students of different races prefer different majors, independent of the state of the business cycle. The results from these alternative specifications are very similar to the main results, with the major-specific coefficients highly correlated with the baseline versions and the relationship between major-specific cyclicality and long-run earnings essentially unchanged. Thus, the cyclicality of major choices does not appear to be driven by changes in these observable characteristics.

Alternatively, one could allow for the major choices of a cohort to depend on *unobservable* characteristics to the extent that they are correlated with the share of the cohort enrolling in or completing college. As examples, perhaps the distribution of family income, the average rigor of high school courses, or the distribution of undergraduate institutions among completers changes with the business cycle. Table 3 presents comparisons resulting from such an exercise. Specifically, we alter Equation (7) by interacting the 38 major-specific dummy variables with a cohort-specific variable that measures the share of the cohort with at least some college (enrollment rates) or with at least a bachelor's degree (completion rates). These interactions therefore allow each major's share to be differentially affected by the unobservable characteristics of a cohort.

Table 3 reports two comparisons between each alternative specification and the baseline results. First, we report the correlation of the major-specific unemployment coefficients with the coefficients reported in Figures 3 and 4. Second, we report the second-stage regression coefficient and R-squared from regressing these coefficients on the long-run earnings of each major.[37] Because long-run earnings are available for all 38 major categories, we use all 38

[37]In Appendix Section A-8, we extend these results further by adding higher order terms of the enrollment

in conducting these robustness checks.[38]

For women, the results are qualitatively similar for all time periods whether or not controls for enrollment or completion are included. For men, the results are more sensitive to the inclusion of these controls, especially when using the entire 1960–2013 time period. Using this sample, the results controlling for enrollment and completion are somewhat different than the baseline results for men, and the relationship between major cyclicality and long-run earnings potential is attenuated. During the early part of this time period, however, enrollment and completion were strongly *procyclical* for men, in contrast to the more recent time period when enrollment and completion have been countercyclical. In particular, the Vietnam War years show a noticeable spike in male enrollment and completion concurrent with low unemployment, which suggests that that period may not have experienced typical cyclical patterns of selection on unobservables. It is possible that, during that era, higher unemployment rates were associated with lower attendance, which led to an increase in the average preparedness of students and a subsequent increase in the earnings capacity of cohorts' completed degrees.

As changes in enrollment were due primarily to the draft rather than the state of the business cycle, we do not believe that the smaller coefficients on median log wage in columns (3) and (4) constitute strong evidence that the unemployment rate affects the major distribution primarily through composition. When we limit the analysis to the Post-Vietnam 1976–2013 time period, the results with and without the composition adjustments are more comparable for men, reinforcing the interpretation that the sensitivity to these controls is driven by the unusual patterns in enrollment and completion in the 1960–1975 period.

Taken as a whole, the results adjusting for cohort composition suggest that most of the change in the distribution of majors occurs among individuals whose college completion decision was unaffected by the business cycle. A portion of the overall change, however, derives from cyclical changes in the observable and unobservable characteristics of the cohorts.

4.3.2 Age of unemployment rate

In our main analysis, we use the unemployment rate for the year a cohort turns 20 as the primary measure of labor market conditions at the time individuals are likely making college major decisions. This choice, necessary although somewhat arbitrary, allows for the fact

and completion rate. These more flexible results are qualitatively similar to the linear results presented here; if anything, they are closer to the baseline results.

[38]Bivariate relationships between the major cyclicality measures and the covariates using all available observations for each covariate are available in Appendix Table A-10.

that not everyone enters college immediately after high school and that majors are often selected partway through undergraduate studies. Figure 8 demonstrates that this choice leads to, if anything, a conservative estimate of the effects of labor market conditions on the degree to which selected majors are higher paying. Each dot represents a coefficient estimate from analysis similar to that reported in Figure 7. We vary the age at which the unemployment rate is measured when calculating major cyclicality (the dependent variable in the regression).[39]

For both genders, the results are strongest for unemployment rates from ages 17–21, with results from earlier or later ages weaker and usually statistically indistinguishable from zero. The consistency of results for this age bracket likely reflects the fact that unemployment rates are strongly positively serially correlated (see Appendix Figure A-8 for a direct analysis of the serial correlation in unemployment rates by age for the sample used in Figure 8). Thus, it is reasonable to interpret the unemployment at age 20 variable as a proxy for unemployment rates around the time of a typical college major decision, and the main results are qualitatively similar regardless of which proxy measure one selects. In fact, if we replace the unemployment rate at age 20 with the average unemployment rate from ages 18–22 (results not shown), the major-specific unemployment coefficients are very strongly correlated with the baseline versions (greater than +0.99 for both men and women) and the second-stage coefficient on long run earnings is similar to the baseline for both genders.

In addition to showing that a cohort's major distribution is unrelated to the unemployment rate at ages far from typical schooling years, it is possible to control for the cohort's experience of the business cycle at other ages. Doing so does not qualitatively affect the results of the analysis. Table 4 presents the results of this robustness exercise, which allows the share of a cohort selecting each major to vary with the unemployment rate at age 10 and at age 30 (or both) in addition to the unemployment rate at age 20. For each specification, we report three statistics: 1) the correlation of the 38 major-specific coefficients on the age-20 unemployment rate with the same coefficients in the baseline specification; 2) The coefficient on median log wage in the second stage; and 3) The R-squared from that same second-stage regression. Column 1 provides the baseline results while column 2 estimates this same specification on the sample for whom unemployment at both control ages is available. Columns 3 and 4 add controls for unemployment at ages 10 and 30, respectively, while column 5 adds

[39] The results for age 20 do not precisely match the coefficient estimate in Table 1 (although they are quite close) because we have limited this analysis to a smaller set of cohorts so that the sample stays consistent in each of the 21 regressions in this figure.

controls for both. The results are remarkably stable across all specifications, reinforcing the conclusion that the observed changes in major choices are due to differential exposure to the business cycle at age 20 rather than to other characteristics of cohorts correlated with differential macroeconomic exposure at other ages.

4.3.3 Local unemployment rates

The analysis above uses national level unemployment rates as the key measure of labor market conditions. For a portion of the included cohorts (those turning 20 from 1976 onward), state level unemployment rates are available as an alternative measure. Using the ACS data, it is possible to link individuals to labor market conditions at age 20 in their state of birth. There is not, however, information on where individuals attended school, nor on where they intended to settle following school.

In Appendix Tables A-14 and A-15, we provide analysis using the local unemployment rates for individuals' state of birth (further discussed in Appendix Section A-10) for men and women, respectively. In these tables, we first repeat the analysis from Equation (7) using state-birth year-major cells (Column 3), and then replace the national unemployment rate with the state-specific unemployment rate (Column 4). The estimated coefficients of major cyclicality are qualitatively similar and highly correlated across the two columns.[40]

4.4 Wages of marginal individuals

A key remaining question is whether individuals who pursue a different major in response to higher unemployment rates reap the earnings benefits associated with those majors. It is possible that the marginal entrants into more difficult majors are less suited to pursuing that line of study and thus receive earnings that are below average. We examine this question in detail in Appendix Section A-11. That analysis is centered on a comparison of residualized wage distributions for four categories of individuals based on whether their majors are pro- or counter-cyclical and whether they graduated in a time of high or low unemployment. We find that the middle of the distribution of earnings is shifted negatively for cohorts that graduated under higher unemployment rates, which is consistent with the literature on the

[40] A specification that exploits only cross-sectional variation around the national business cycle produces estimates that are extremely noisy, suggestive of insufficient variation in relative deviations at the state level, or indicating the importance of national labor market conditions in major choice. Ersoy (2020) provides clearer evidence that college major choice responded to regional heterogeneity in the severity of the Great Recession.

effects of graduating in a recession (e.g., Kahn 2010).

We find no evidence, however, that individuals with countercyclical majors who graduated in a high unemployment environment are more likely to be in the left tail of the distribution. Similarly, we find no evidence that individuals with procyclical majors who graduated in times of low unemployment are especially likely to be in the right tail of the earnings distribution. Thus, individuals who choose a different major as a result of the state of the business cycle appear to have earnings similar to the inframarginal graduates with the same major. It seems unlikely, therefore, that the business cycle induces students to study fields for which they are poorly matched. Instead, it seems more likely that students choose higher-earning fields from the set of potential majors in which they are likely to be successful, both during school and beyond.

In Appendix Section A-12, we also examine time series variation in the likelihood of working in the most appropriate field for majors that gain share during recessions. In particular, we look to see how often Engineering majors work as engineers and how often Nursing majors work as nurses. If anything, the results suggest that cohorts who chose these majors during times of higher unemployment are *more likely* to work in the expected field. This additional evidence supports the conclusion that individuals who choose new majors experience earnings gains as a result.

4.4.1 Implications for Graduating in a Recession

Our analysis establishes that some students shift into more remunerative majors during recessions and that students who switch into these majors enjoy earnings similar to what typical graduates with those degrees earn. Previous estimates of the negative effect of graduating in a recession are, therefore, an underestimate of the direct effect of weaker employer demand on earnings because these effects are partially counterbalanced by a re-distribution of graduates toward more lucrative degrees. Appendix Section A-13 provides a back-of-the-envelope calculation using the cyclicality results from Section 3.2 to show that, if no students changed majors, the effect of graduating in a recession would be roughly 10 percent larger. Overall, these results reveal an important dimension of heterogeneity in experiencing a recession around the time of undergraduate study. A minority of students choose a higher-earnings major, likely improving their lifetime earnings. Others experience only the negative impact of the decline in employer demand, which is somewhat larger in magnitude than the average effect previous studies have estimated.

5 Conclusion

Personal experience with transitory economic downturns shapes individuals' preferences and expectations in surprisingly long-lasting ways. In this paper, we take advantage of the release of unprecedented data on degree recipients in the United States to investigate the impact of economic conditions on the choice of college major, a central component of "permanent" human capital. Using data on college major choice from the American Community Survey for cohorts graduating between 1960 and 2013, we show that the distribution of college majors changes substantially in response to the business cycle. The sample size and long time dimension of our dataset allow us to control comprehensively for fixed and slow-moving structural changes to the demand for and components of college majors over this fifty year period. We estimate that a one percentage point increase in the unemployment rate leads to a 4.2 percentage point total reallocation of majors for women, and a 2.9 percentage point reallocation for men.

The recession-induced reallocation in college majors shifts the distribution toward fields of study that are more challenging, require more math, and are higher paying. Conditional on long-run earnings, we show that students move into more difficult, more male-dominated (among women), and more career-oriented fields. These additional results suggest that in response to anticipated weak labor demand upon graduation, students either devote more resources to learning about the career potential of majors or become more sensitive to the signal that their major sends about their ability to potential employers. Given that many college students, and especially female college students, respond to economic downturns by moving into STEM fields, other similarly-timed interventions may yield comparable results in periods with stronger labor market prospects.[41]

This study provides direct evidence that the state of the business cycle affects students' choices about what to study. In doing so, we have identified the combined effect of multiple mechanisms activated during downturns including changing incentives to gather accurate information, altering the framing for the purpose of schooling, directly changing the returns to different majors, and potentially creating an arms race for credentials among new college graduates. We leave to future research to uncover which of these channels is most important and whether policymakers can develop alternative interventions to leverage these same channels throughout the business cycle.

[41] On a related point, Jacobson, LaLonde, and Sullivan (2005) find that displaced workers obtain sizable returns to math and science community college courses, and that the return is more than twice as large for women.

References

Altonji, Joseph G. 1993. The demand for and return to education when education outcomes are uncertain. *Journal of Labor Economics* 11 (1):48–83.

Altonji, Joseph G., Erica Blom, and Costas Meghir. 2012. Heterogeneity in human capital investments: High school curriculum, college major, and careers. *Annual Review of Economics* 4 (1):185–223.

Altonji, Joseph G., Lisa B. Kahn, and Jamin D. Speer. 2016. Cashier or consultant? Entry labor market conditions, field of study, and career success. *Journal of Labor Economics* 34 (S1):S361–S401.

Arcidiacono, Peter. 2004. Ability sorting and the returns to college major. *Journal of Econometrics* 121 (1):343–375.

Arcidiacono, Peter, Esteban M. Aucejo, and V. Joseph Hotz. 2016. University differences in the graduation of minorities in STEM fields: Evidence from California. *American Economic Review* 106 (3):525–562.

Arcidiacono, Peter, V. Joseph Hotz, and Songman Kang. 2012. Modeling college major choices using elicited measures of expectations and counterfactuals. *Journal of Econometrics* 166 (1):3–16.

Baker, Rachel, Eric Bettinger, Brian Jacob, and Ioana Marinescu. 2018. The effect of labor market information on community college students' major choice. *Economics of Education Review* 65:18 – 30.

Barr, Andrew and Sarah E. Turner. 2013. Expanding enrollments and contracting state budgets: The effect of the great recession on higher education. *The Annals of the American Academy of Political and Social Science* 650:168–193.

Bedard, Kelly and Douglas A. Herman. 2008. Who goes to graduate/professional school? The importance of economic fluctuations, undergraduate field, and ability. *Economics of Education Review* 27 (2):197–210.

Beffy, Magali, Denis Fougère, and Arnaud Maurel. 2012. Choosing the field of study in postsecondary education: do expected earnings matter? *Review of Economics and Statistics* 94 (1):334–347.

Berger, Mark C. 1988. Predicted future earnings and choice of college major. *Industrial and Labor Relations Review* 41 (3):418–429.

Betts, Julian R. 1996. What do students know about wages? Evidence from a survey of undergraduates. *Journal of Human Resources* 31 (1):27–56.

Betts, Julian R. and Laurel L. McFarland. 1995. Safe port in a storm: The impact of labor market conditions on community college enrollments. *Journal of Human Resources* 30:741–765.

Blau, Francine D. and Lawrence M. Kahn. 2007. Changes in the labor supply behavior of married women: 1980-2000. *Journal of Labor Economics* 25 (3):393–438.

Blom, Erica. 2012. Labor market determinants of college major. PhD diss., Department of Economics, Yale University.

Bound, John, Michael F. Lovenheim, and Sarah E. Turner. 2010. Why have college completion rates declined? An analysis of changing student preparation and collegiate resources. *American Economic Journal: Applied Economics* 2 (3):129–57.

Bradley, Elizabeth S. 2012. The effect of the business cycle on freshman major choice. MPRA Paper 42412, University Library of Munich, Germany.

Brown, Charles and Mary Corcoran. 1997. Sex-based differences in school content and the male-female wage gap. *Journal of Labor Economics* 15 (3):431–465.

Bureau of Labor Statistics. 2020. (Unadj) Unemployment rate, series ID LNU04000000. URL `https://data.bls.gov/timeseries/LNU04000000`.

Buser, Thomas, Muriel Niederle, and Hessel Oosterbeek. 2014. Gender, competitiveness, and career choices. *Quarterly Journal of Economics* 129 (3):1409–1447.

Card, David and A. Abigail Payne. 2017. High school choices and the gender gap in stem. NBER Working Paper 23769, National Bureau of Economic Research, Cambridge, MA.

Charles, Kerwin K., Erik Hurst, and Matthew J. Notowidigdo. 2018. Housing booms and busts, labor market opportunities, and college attendance. *American Economic Review* 108 (10):2947–94.

Christian, Michael S. 2007. Liquidity constraints and the cyclicality of college enrollment in the united states. *Oxford Economic Papers* 59 (1):141–169.

Conlon, John J. 2019. Major malfunction: A field experiment correcting undergraduates' beliefs about salaries. *Journal of Human Resources* 0317-8599R2. Published ahead of print September 16, 2019, doi:10.3368/jhr.56.3.0317-8599R2.

Currie, Janet and Hannes Schwandt. 2014. Short- and long-term effects of unemployment on fertility. *Proceedings of the National Academy of Sciences* 111 (41):14734–14739.

Davis, Steven J. and John Haltiwanger. 1990. Gross job creation and destruction: Microeconomic evidence and macroeconomic implications. In *NBER Macroeconomics Annual*, vol. 5, ed. Olivier J. Blanchard and Stanley Fischer. MIT Press, 123–186.

Dellas, Harris and Plutarchos Sakellaris. 2003. On the cyclicality of schooling: Theory and evidence. *Oxford Economic Papers* 55 (1):148–172.

Denning, Jeffrey T. and Patrick Turley. 2017. Was that SMART? institutional financial incentives and field of study. *Journal of Human Resources* 52 (1):152–186.

Dynarski, Susan. 2008. Building the stock of college-educated labor. *Journal of Human Resources* 43 (3):576–610.

Ehrenberg, Ronald G. 2010. Analyzing the factors that influence persistence rates in stem field, majors: Introduction to the symposium. *Economics of Education Review* 29 (6):888–891.

Ersoy, Fulya Y. 2020. The effects of the great recession on college majors. *Economics of Education Review* 77:102018.

Freeman, Richard B. 1976. A cobweb model of the supply and starting salary of new engineers. *Industrial and Labor Relations Review* 29 (2):236–248.

Gemici, Ahu and Matthew Wiswall. 2014. Evolution of gender differences in post-secondary human capital investments: College majors. *International Economic Review* 55 (1):23–56.

Giuliano, Paola and Antonio Spilimbergo. 2014. Growing up in a recession. *The Review of Economic Studies* 81 (2):787–817.

Gneezy, Uri, Muriel Niederle, and Aldo Rustichini. 2003. Performance in competitive environments: Gender differences. *Quarterly Journal of Economics* 118 (3):1049–1074.

Goldin, Claudia. 2013. Notes on women and the undergraduate economics major. *CSWEP Newsletter* (Summer):4–6, 15.

———. 2015. A pollution theory of discrimination: Male and female differences in occupations and earnings. In *Human capital in history: The american record*, ed. Leah P. Boustan, Carola Frydman, and Robert A. Margo. Chicago: University of Chicago Press.

Goldin, Claudia and Lawrence F. Katz. 2009. *The race between education and technology*. Cambridge, MA: Harvard University Press.

Goldin, Claudia, Lawrence F. Katz, and Ilyana Kuziemko. 2006. The homecoming of american college women: The reversal of the college gender gap. *Journal of Economic Perspectives* 20 (4):133–156.

Hastings, Justine S., Christopher A. Neilson, and Seth D. Zimmerman. 2014. Are some degrees worth more than others? Evidence from college admission cutoffs in Chile. NBER Working Paper 19241, National Bureau of Economic Research, Cambridge, MA.

———. 2015. The effects of earnings disclosure on college enrollment decisions. NBER Working Paper 21300, National Bureau of Economic Research, Cambridge, MA.

Heckman, James J. 1993. What has been learned about labor supply in the past twenty years? *The American Economic Review* 83 (2):116–121.

Hershbein, Brad J. 2012. Graduating high school in a recession: Work, education, and home production. *The BE Journal of Economic Analysis & Policy* 12 (1):1–32.

Hoynes, Hilary, Douglas L. Miller, and Jessamyn Schaller. 2012. Who suffers during recessions? *Journal of Economic Perspectives* 26 (3):27–48.

Jacobson, Louis, Robert LaLonde, and Daniel G. Sullivan. 2005. Estimating the returns to community college schooling for displaced workers. *Journal of Econometrics* 125 (1):271–304.

Johnson, Matthew T. 2013. The impact of business cycle fluctuations on graduate school enrollment. *Economics of Education Review* 34:122–134.

Kahn, Lisa B. 2010. The long-term labor market consequences of graduating from college in a bad economy. *Labour Economics* 17 (2):303–316.

Killingsworth, Mark R. and James J. Heckman. 1986. Chapter 2 Female labor supply: A survey. In *Handbook of Labor Economics*, vol. 1, ed. Orley Ashenfelter and Richard Layard. Amsterdam: Elsevier.

Kirkebøn, Lars J., Edwin Leuven, and Magne Mogstad. 2016. Field of study, earnings, and self-selection. *Quarterly Journal of Economics* 131 (3):1057–1111.

Light, Audrey and Wayne Strayer. 2000. Determinants of college completion: School quality or student ability? *Journal of Human Resources* 35 (2):299–332.

Liu, Shimeng, Weizeng Sun, and John V. Winters. 2019. Up in STEM, down in business: Changing college major decisions with the great recession. *Contemporary Economic Policy* 37 (3):476–491.

Long, Bridget Terry. 2015. The financial crisis and college enrollment: How have students and their families responded? In *How the financial crisis and great recession affected higher education*, ed. Jeffrey R. Brown and Caroline M. Hoxby. Chicago: University of Chicago Press, 209–233.

Long, Mark C., Dan Goldhaber, and Nick Huntington-Klein. 2015. Do completed college majors respond to changes in wages? *Economics of Education Review* 49:1–14.

Lordan, Grace and Jörn-Steffen Pischke. 2016. Does Rosie like riveting? Male and female occupational choices. NBER Working Paper 22495, National Bureau of Economic Research, Cambridge, MA.

Malmendier, Ulrike and Stefan Nagel. 2011. Depression babies: Do macroeconomic experiences affect risk taking? *Quarterly Journal of Economics* 126 (1):373–416.

———. 2016. Learning from inflation experiences. *Quarterly Journal of Economics* 131 (1):53–87.

Montmarquette, Claude, Kathy Cannings, and Sophie Mahseredjian. 2002. How do young people choose college majors? *Economics of Education Review* 21 (6):543–556.

Nagler, Markus, Marc Piopiunik, and Martin R. West. 2017. Weak markets, strong teachers: Recession at career start and teacher effectivenes. NBER Working Paper 21393, National Bureau of Economic Research, Cambridge, MA.

Niederle, Muriel and Lise Vesterlund. 2007. Do women shy away from competition? Do men compete too much? *Quarterly Journal of Economics* 122 (3):1067–1101.

Oreopoulos, Philip, Till von Wachter, and Andrew Heisz. 2012. The short- and long-term career effects of graduating in a recession. *American Economic Journal: Applied Economics* 4 (1):1–29.

Oyer, Paul. 2006. Initial labor market conditions and long-term outcomes for economists. *Journal of Economic Perspectives* 20 (3):143–160.

———. 2008. The making of an investment banker: Stock market shocks, career choice, and lifetime income. *The Journal of Finance* 63 (6):2601–2628.

Ruggles, Steven, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas, and Matthew Sobek. 2020. Integrated public use microdata series: Version 10.0. [Machine-readable database]. Minneapolis, MN: University of Minnesota.

Ruhm, Christopher J. 2000. Are recessions good for your health? *Quarterly Journal of Economics* 115 (2):617–650.

Ryoo, Jaewoo and Sherwin Rosen. 2004. The engineering labor market. *Journal of Political Economy* 112 (S1):S110–S140.

Sakellaris, Plutarchos and Antonio Spilimbergo. 2000. Business cycles and investment in human capital: international evidence on higher education. *Carnegie-Rochester Conference Series on Public Policy* 52:221–256.

Shu, Pian. 2016. Innovating in science and engineering or 'cashing in' on Wall Street? evidence on elite STEM talent. Unit Working Paper 16-067, Harvard Business School Technology & Operations Mgt.

Spence, A. Michael. 1973. Job market signaling. *Quarterly Journal of Economics* 87 (3):355–374.

Stinebrickner, Ralph and Todd R. Stinebrickner. 2014. A major in science? Initial beliefs and final outcomes for college major and dropout. *The Review of Economic Studies* 81 (1):426–472.

Turner, Sarah E. and William G. Bowen. 1999. Choice of major: The changing (unchanging) gender gap. *Industrial and Labor Relations Review* 52 (2):289–313.

Urrutia, Amber Q. 2016. College major and the economy: The impact of labor market conditions on field of study. PhD diss., University of California, Riverside.

Wee, Shu Lin. 2013. Delayed learning and human capital accumulation: The cost of entering the job market during a recession. Unpublished manuscript, Department of Economics, University of Maryland.

Weinstein, Russell. 2020. Local labor markets and human capital investments. *Journal of Human Resources* 58 (1):1119–10566R2. Published ahead of print August 6, 2020, doi:10.3368/jhr.58.1.1119-10566R2.

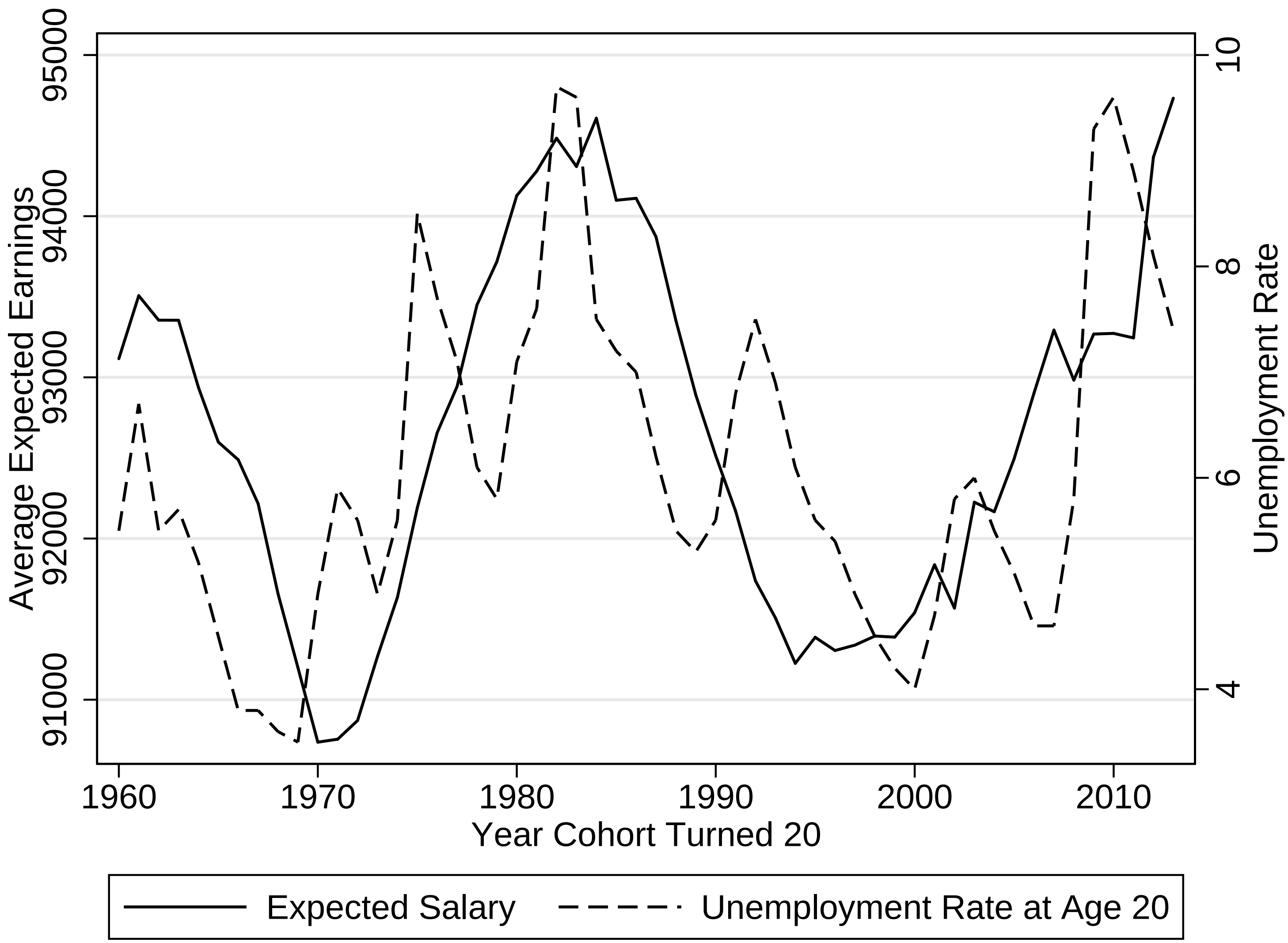
Wiswall, Matthew and Basit Zafar. 2015a. Determinants of college major choice: Identification using an information experiment. *Review of Economic Studies* 82 (2):791–824.

———. 2015b. How do college students respond to public information about earnings? *Journal of Human Capital* 9 (2):117–169.

Zafar, Basit. 2011. How do college students form expectations? *Journal of Labor Economics* 29 (2):301–348.

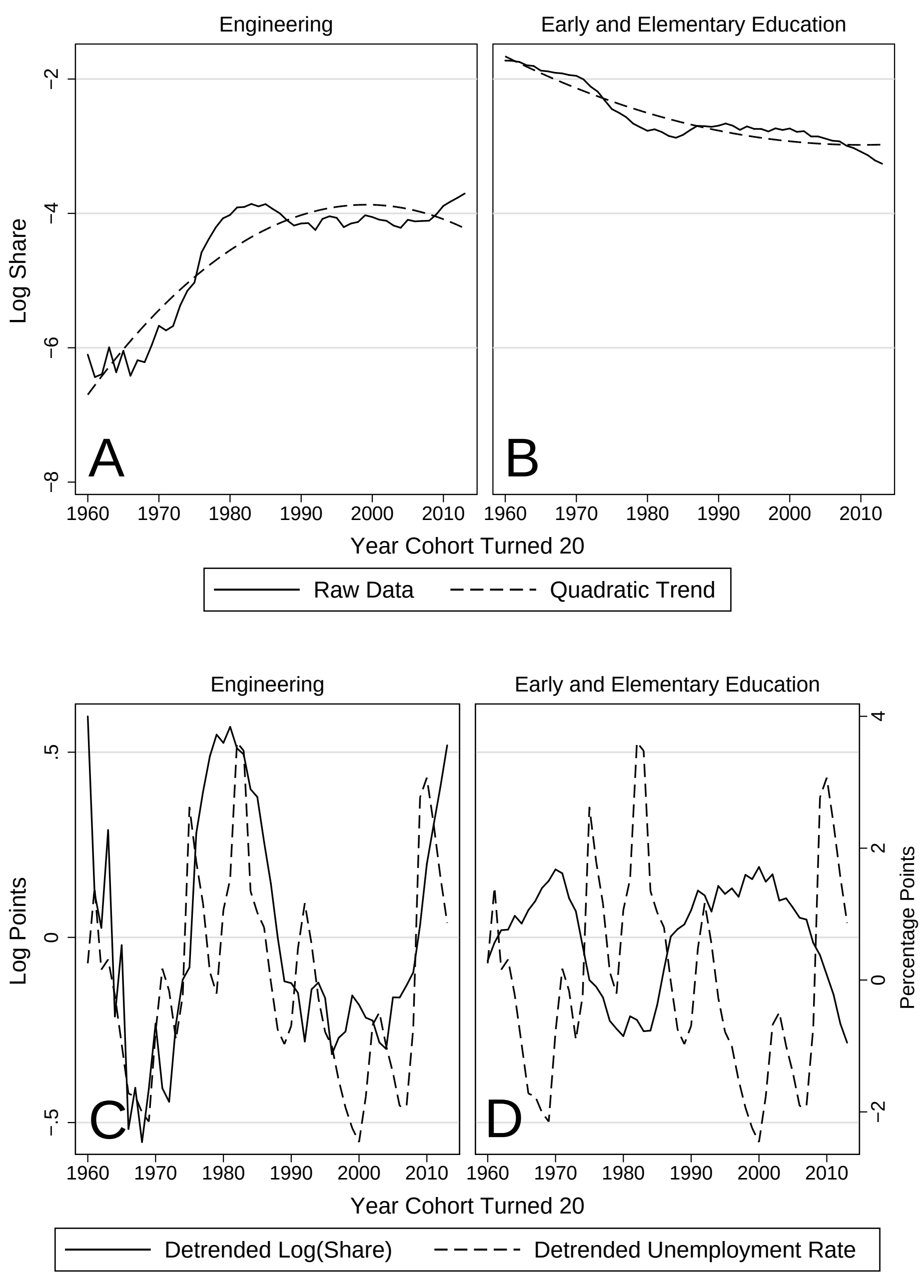
———. 2013. College major choice and the gender gap. *Journal of Human Resources* 48 (3):545–595.

Figure 1: Business Cycles and College Major Composition, as Measured by Full-Time Earnings, by Cohort



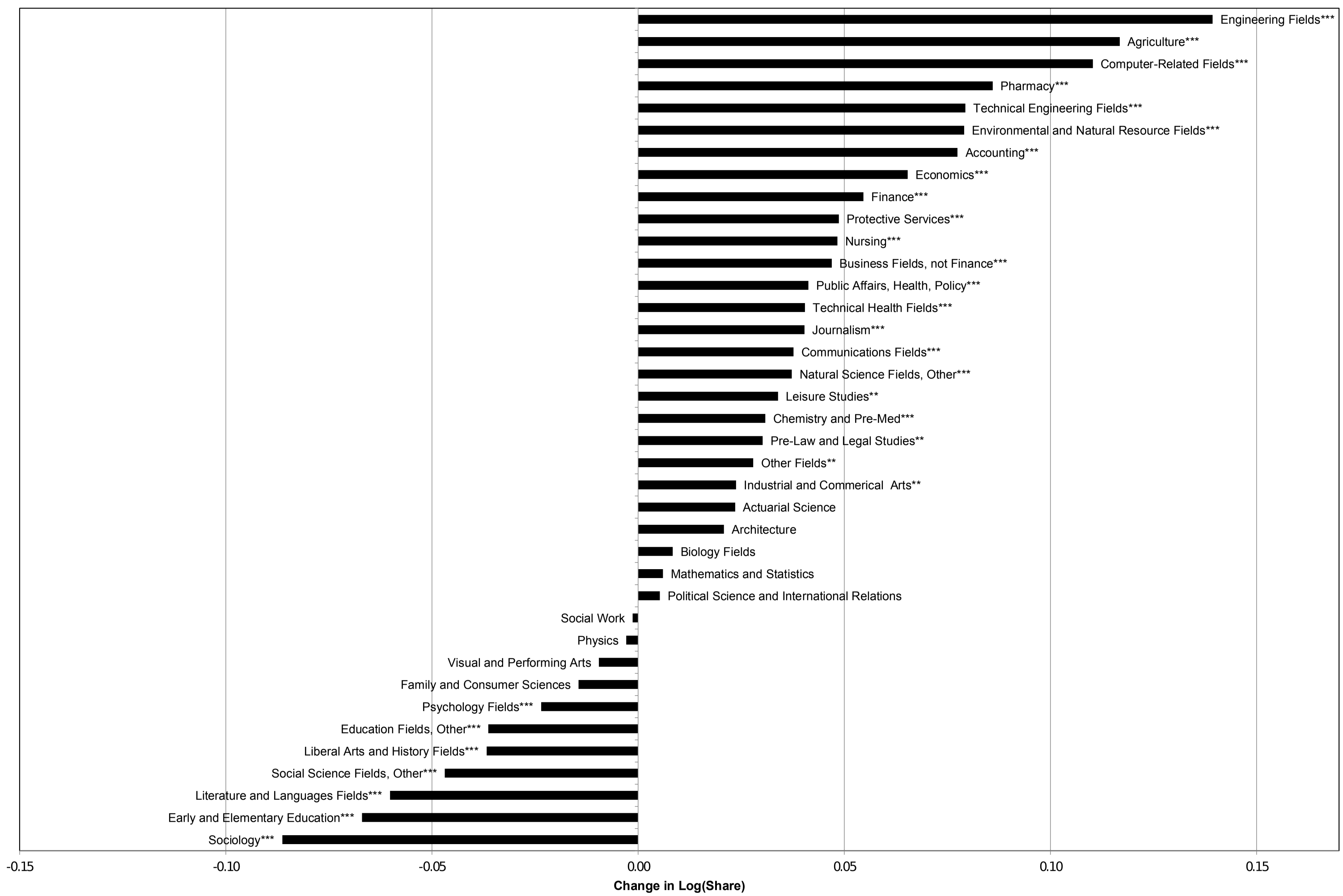
Source: Bureau of Labor Statistics (unemployment rate) and authors' calculations from IPUMS 2009–2018 (average expected earnings among employed). Average expected earnings for a field of study are based on 2009–2018 earnings data among men ages 35-45 who are employed full time (at least 35 hours per week), full year (50-52 weeks per year). Earnings are adjusted for inflation to constant 2010 dollars. Average expected earnings is a weighted average of these major-specific average earnings levels using each birth cohort's share of college graduate men who completed each major as weights.

Figure 2: Raw and Detrended Log-Shares of Cohort Selecting Major



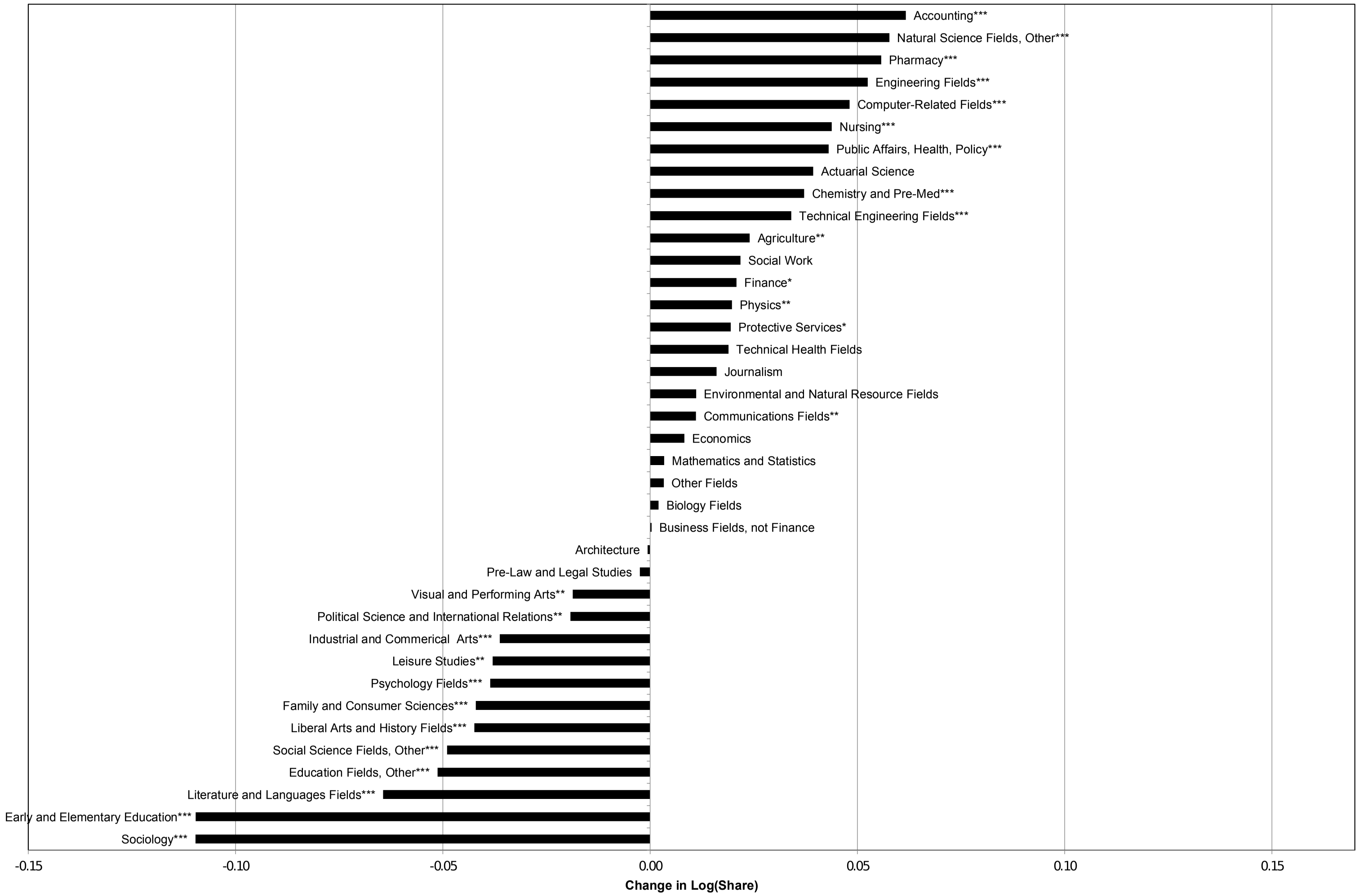
Data sources: BLS and authors' calculations from 2009–2018 ACS data. This analysis is based on the fields of study for birth cohorts of women who completed college degrees. Panels A and B show the raw data and best fit quadratic trends for the log(share) of graduates completing degrees in Engineering and Early and Elementary Education, respectively. Panels C and D show the time series of the residual log(share) variable after removing the trend as well as a similarly (quadratic) de-trended time series of the national unemployment rate.

Figure 3: Change in Log(Share) Due to 1 ppt Increase in Unemployment Rate – Women



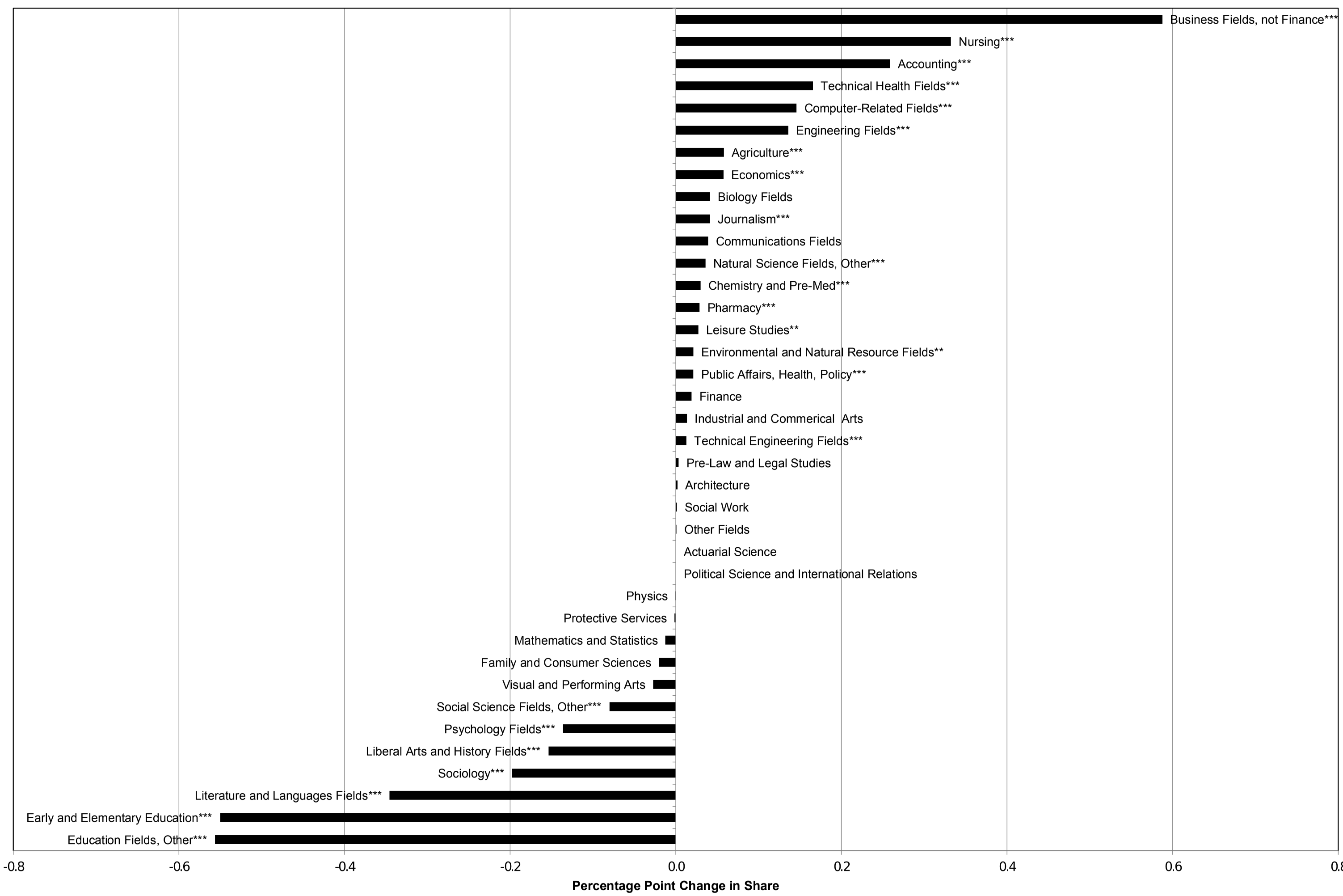
Data sources: BLS and authors' calculations from 2009–2018 ACS data. These coefficients represent the change in log(share) of a birth cohort selecting a given major category due to a one percentage point increase in the unemployment rate and are based on Equation 7, which includes major fixed effects and major-specific trends. The specifications are run separately for men and women – see Figure 4 for the results for men. Stars next to the bars showing the size of the coefficient for each major represent the p-value from a test of the null that the coefficient is zero ***$p < 0.01$, **$p < 0.05$ *$p < 0.10$. See Appendix Table A-1 for a list of constituent degree fields in each of these groups of majors. Appendix Table A-3 contains a complete set of numerical results, including standard errors for the coefficient estimates and the long-run average shares for each major separately by gender.

Figure 4: Change in Log(Share) Due to 1 ppt Increase in Unemployment Rate – Men



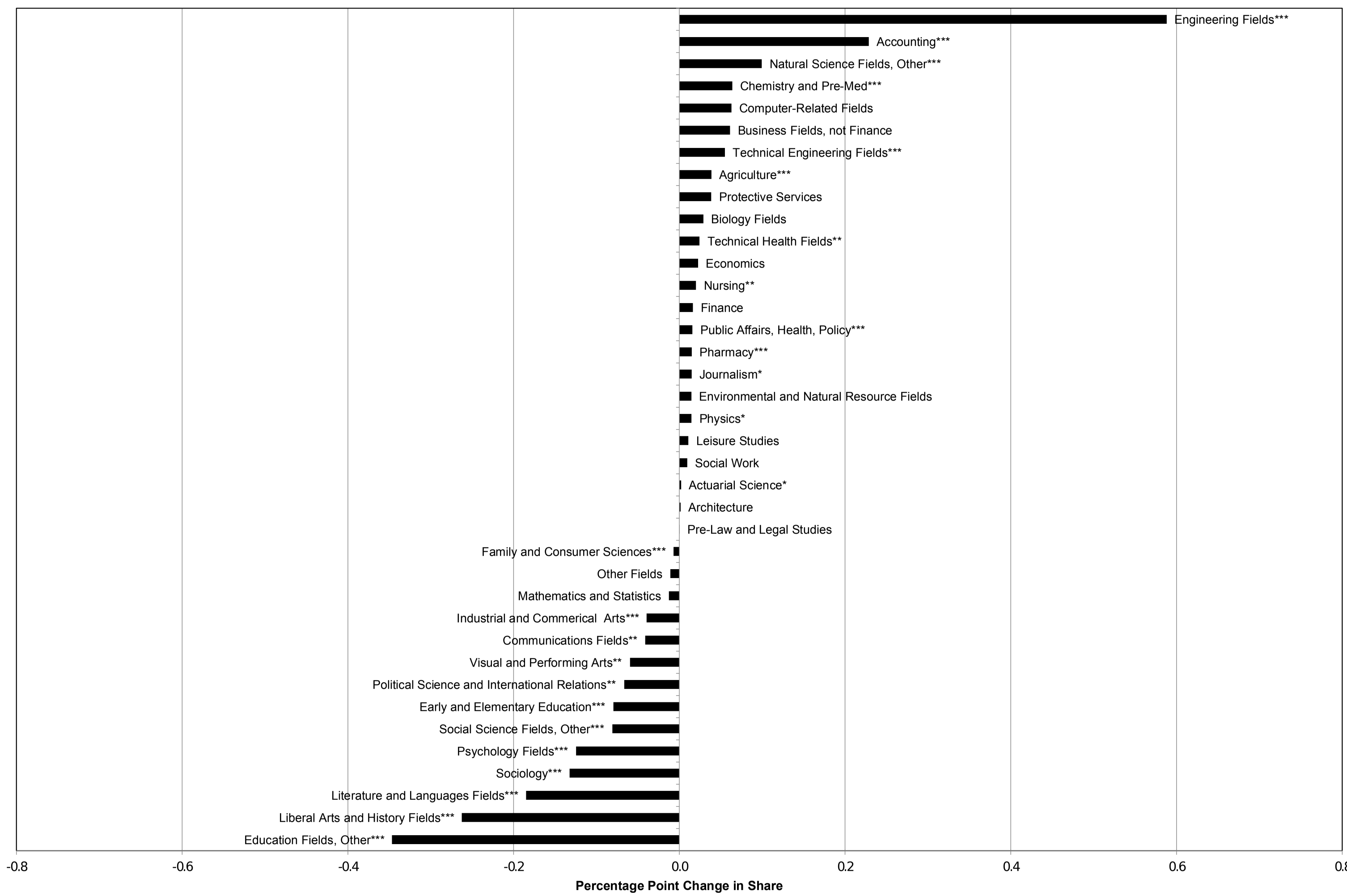
Data sources: BLS and authors' calculations from 2009–2018 ACS data. These coefficients represent the change in log(share) of a birth cohort selecting a given major category due to a one percentage point increase in the unemployment rate and are based on Equation 7, which includes major fixed effects and major-specific trends. The specifications are run separately for men and women – see Figure 3 for the results for women. Stars next to the bars showing the size of the coefficient for each major represent the p-value from a test of the null that the coefficient is zero ***$p < 0.01$, **$p < 0.05$ *$p < 0.10$. See Appendix Table A-1 for a list of constituent degree fields in each of these groups of majors. Appendix Table A-3 contains a complete set of numerical results, including standard errors for the coefficient estimates and the long-run average shares for each major separately by gender.

Figure 5: Change in Share Due to 1 ppt Increase in Unemployment Rate – Women



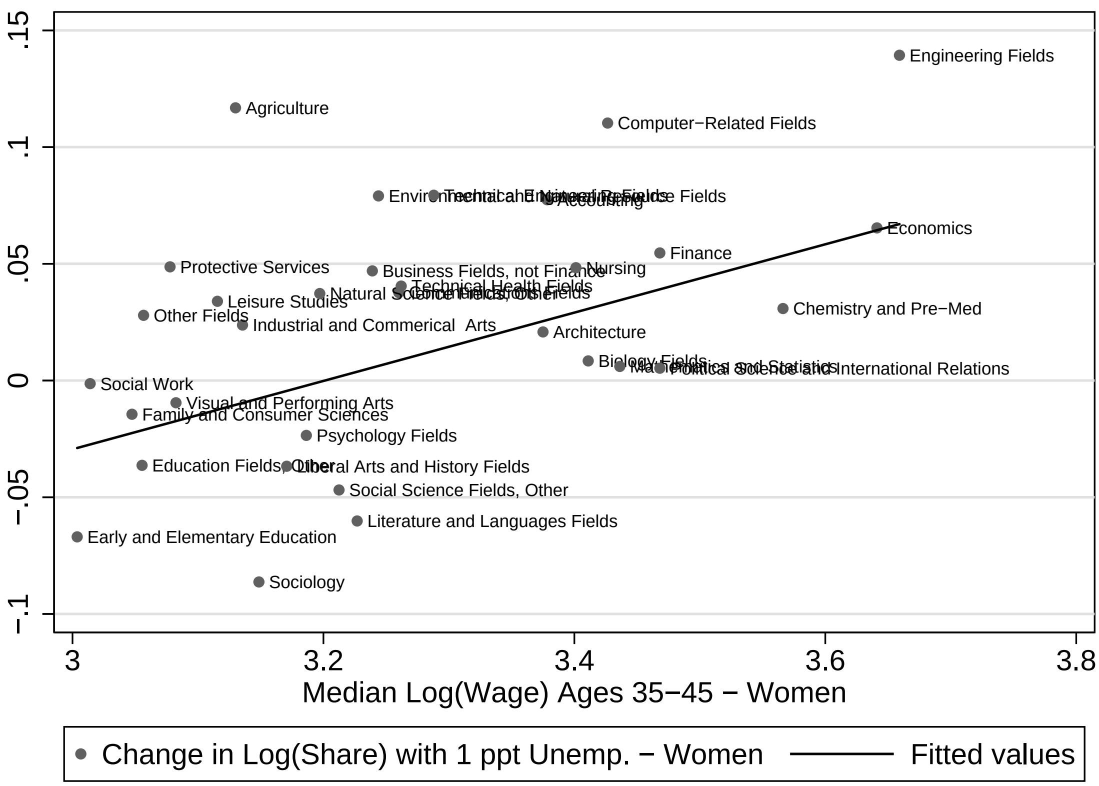
Data sources: BLS and authors' calculations from 2009–2018 ACS data. These coefficients represent the change in share of a birth cohort selecting a given major category due to a one percentage point increase in the unemployment rate and are based on Equation 7, which includes major fixed effects and major-specific trends. The specifications are run separately for men and women – see Figure 4 for the results for men. Stars next to the bars showing the size of the coefficient for each major represent the p-value from a test of the null that the coefficient is zero ***$p < 0.01$, **$p < 0.05$ *$p < 0.10$. See Appendix Table A-1 for a list of constituent degree fields in each of these groups of majors. Appendix Table A-3 contains a complete set of numerical results, including standard errors for the coefficient estimates and the long-run average shares for each major separately by gender.

Figure 6: Change in Share Due to 1 ppt Increase in Unemployment Rate – Men



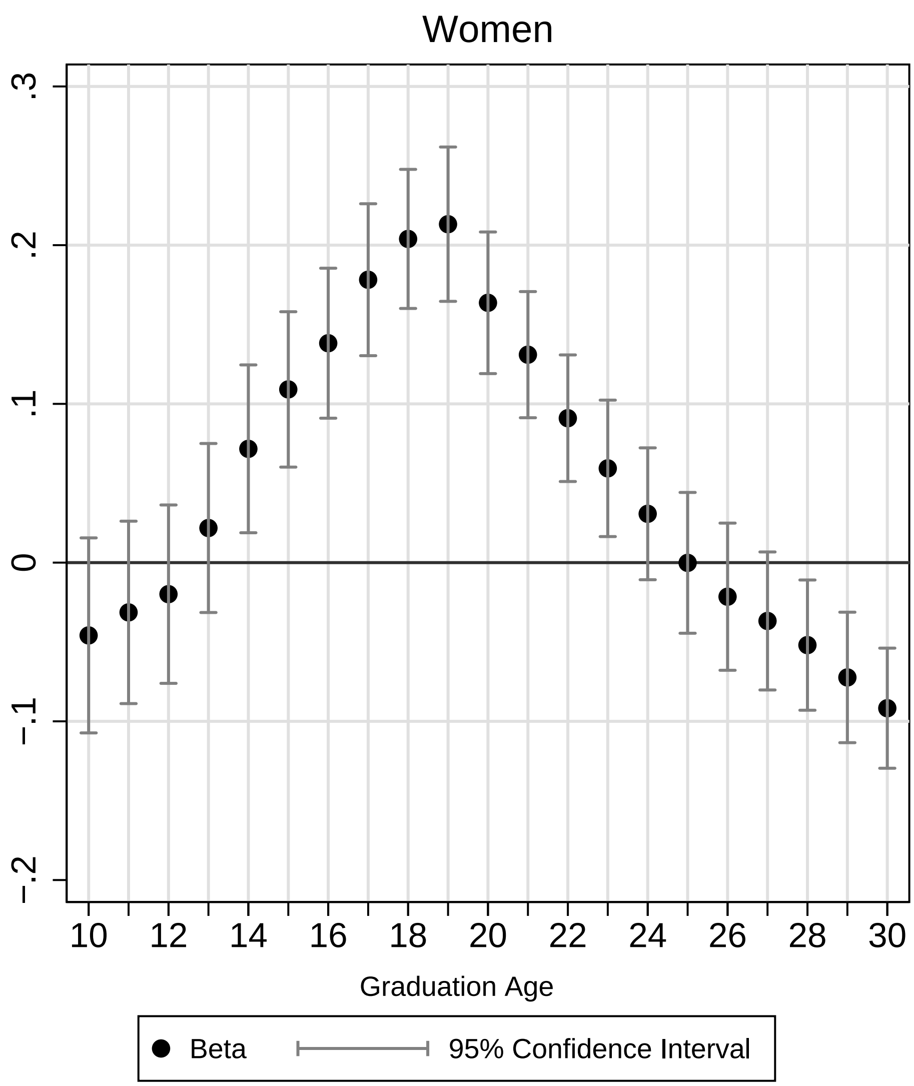
Data sources: BLS and authors' calculations from 2009–2018 ACS data. These coefficients represent the change in share of a birth cohort selecting a given major category due to a one percentage point increase in the unemployment rate and are based on Equation 7, which includes major fixed effects and major-specific trends. The specifications are run separately for men and women – see Figure 3 for the results for women. Stars next to the bars showing the size of the coefficient for each major represent the p-value from a test of the null that the coefficient is zero ***$p < 0.01$, **$p < 0.05$ *$p < 0.10$. See Appendix Table A-1 for a list of constituent degree fields in each of these groups of majors. Appendix Table A-3 contains a complete set of numerical results, including standard errors for the coefficient estimates and the long-run average shares for each major separately by gender.

Figure 7: Relationship Between Long-Run Earnings and Major Share Cyclicality



The dependent variable is the major-specific coefficient on the unemployment rate from the analysis in Figure 3. The fitted line represents the predicted values from a weighted regression, using the inverse of the sampling variance of the dependent variable (estimated using the bootstrapping procedure discussed in the text). Long-Run Earnings are the median log(earnings) of women ages 35-45 working full-time, full-year in 2009–2018.

Figure 8: Relationship between Long-Run Earnings and Major Cyclicality, by Reference Age of Unemployment



Data sources: BLS and authors' calculations from 2009–2018 ACS data. The figure plots coefficient estimates from separate regressions of the second stage relationship between long-run earnings and major cyclicality, varying the age at which the unemployment rate is measured when calculating major cyclicality. The confidence intervals are plotted using the bootstrap standard errors. In calculating bootstrap SEs, the sample only includes the cohorts born in 1960–1989 (as opposed to the original sample of the 1960–1993 birth cohorts) such that every cohort in the sample has corresponding unemployment rates for the full range of ages.

Table 1: Correlates of Cyclical Changes in Major Shares – Labor Market Prospects

	Women			Men		
	(1)	(2)	(3)	(4)	(5)	(6)
Median Log(Wage) Ages 35-45	0.146 ***	0.127 ***	0.079 ***	0.123 ***	0.119 ***	0.091 ***
	(0.021)	(0.016)	(0.012)	(0.021)	(0.017)	(0.018)
Number of Job Interviews w/in First Year		0.006 **	0.009 ***		0.001	0.000
		(0.003)	(0.003)		(0.003)	(0.003)
Share Employed at 1 Year			0.094 ***			0.112 ***
			(0.022)			(0.028)
Share in Unrelated Jobs in First Year			-0.161 ***			-0.116 ***
			(0.022)			(0.016)
Observations	32	32	32	32	32	32
R-squared	0.306	0.339	0.647	0.313	0.315	0.509

Authors' calculations from ACS and B&B data. The dependent variable in each regression is the major-specific coefficient on the unemployment rate from Equation 7 using Log(Share) as the dependent variable. These coefficient estimates are available in Figures 3 and 4. Earnings and FTFY are calculated separately by gender. All other variables are calculated based on all graduates in the major category. See Appendix Table A-1 for a list of majors. Regression samples are limited to a consistent set of majors for which all included covariates are available. Excluded majors are Actuarial Science; Journalism; Pre-Law/Legal Studies; Pharmacy; Physics; and Public Affairs, Health, Policy. Appendix Table A-9 provides summary statistics, including means, standard deviations and the number of valid observations for each of these covariates. Observations are weighted by the inverse of the estimated variance of the dependent variable, which is calculated using the bootstrapping procedure described in the text. Bootstrapped standard errors in parentheses - see text for bootstrapping details. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 2: Correlates of Cyclical Changes in Major Shares *Conditional* on Labor Market Prospects

Characteristic of Major	Women			Men		
Career Concerns						
Share with a Grad Degree (Age 35-45)	-0.162	***	(0.022)	-0.095	***	(0.024)
HHI of Occupations (Age 35-45)	-0.044	*	(0.024)	-0.057	***	(0.019)
Share Working FTFY (35-45)	0.240	***	(0.045)	0.228	***	(0.054)
Difficulty						
Average GPA for Major Courses	-0.228	***	(0.035)	-0.158	***	(0.029)
Median SAT Math Score/100	-0.027	***	(0.006)	-0.016	***	(0.004)
Average Math GPA	-0.029	***	(0.007)	-0.054	***	(0.008)
Other Non-Pecuniary Factors						
Long-run Average Female Share of Major	-0.094	***	(0.016)	-0.069	***	(0.016)
Share Living in State of Birth (Age 35-45)	0.088	**	(0.035)	0.039		(0.024)

Authors' calculations from ACS and B&B data. The dependent variable in each regression is the major-specific coefficient on the unemployment rate from Equation 7 using Log(Share) as the dependent variable. These coefficient estimates are available in Figures 3 and 4. Earnings and FTFY are calculated separately by gender. All other variables are calculated based on all graduates in the major category. See Appendix Table A-1 for a list of majors. Regression samples are limited to a consistent set of majors for which all included covariates are available. Excluded majors are Actuarial Science; Journalism; Pre-Law/Legal Studies; Pharmacy; Physics; and Public Affairs, Health, Policy. Appendix Table A-9 provides summary statistics, including means, standard deviations and the number of valid observations for each of these covariates. Observations are weighted by the inverse of the estimated variance of the dependent variable, which is calculated using the bootstrapping procedure described in the text. Bootstrapped standard errors in parentheses - see text for bootstrapping details. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Results Robust to Inclusion of Controls for Cohort Enrollment and Completion

	Baseline	Non-Parametric with Bandwidth=7		
	(1)	(2)	(3)	(4)
Panel A: Women				
1960-2013				
Correlation with Baseline Beta	1	0.928	0.884	0.777
Coefficients on Median Log Wage	0.135	0.097	0.085	0.064
R-squared	0.296	0.316	0.197	0.129
1976-2013				
Correlation with Baseline Beta	1	0.595	0.549	0.518
Coefficients on Median Log Wage	0.084	0.063	0.056	0.050
R-squared	0.387	0.370	0.300	0.243
Panel B: Men				
1960-2013				
Correlation with Baseline Beta	1	0.931	0.657	0.495
Coefficients on Median Log Wage	0.114	0.090	0.033	0.040
R-squared	0.306	0.312	0.052	0.094
1976-2013				
Correlation with Baseline Beta	1	0.876	0.787	0.702
Coefficients on Median Log Wage	0.079	0.088	0.073	0.052
R-squared	0.400	0.338	0.236	0.146
Control for Enrollment Rates	N	N	Y	N
Control for Completion Rates	N	N	N	Y

Authors' calculations from ACS and B&B data. The table presents sensitivity analysis to the inclusion of controls for cohort-specific enrollment and completion rates. Separately for men and women, the table provides the correlation with the baseline distribution of cyclicality, the second-stage coefficient on median log wage, and the R-squared from the second-stage regression. Column (1) provides baseline specifications using all 38 majors; the coefficient on Median Log Wage is identical to the coefficient reported in Appendix Table A-8. Column (2) provides the relationships for the non-parametric estimation approach with a seven-year bandwidth (see Appendix A-2 for details). Columns (3) and (4) add cohort-specific controls for four-year college enrollment rates and completion rates, respectively.

Table 4: Results Robust to Inclusion of Controls for Unemployment at Ages 10 and 30

	Grad Year: 1960-2013	Grad Year: 1960-2009			
	(1)	(2)	(3)	(4)	(5)
Panel A: Women					
Correlation with Baseline Beta	1	0.978	0.965	0.981	0.977
Coefficients on Median Log Wage	0.135	0.142	0.136	0.127	0.121
R-squared	0.296	0.330	0.357	0.289	0.316
Panel B: Men					
Correlation with Baseline Beta	1	0.961	0.949	0.965	0.958
Coefficients on Median Log Wage	0.114	0.108	0.102	0.095	0.088
R-squared	0.307	0.295	0.308	0.242	0.252
Control for Unemployment at Age 10	N	N	Y	N	Y
Control for Unemployment at Age 30	N	N	N	Y	Y

Authors' calculations from ACS and B&B data. The table presents sensitivity analysis to the inclusion of controls for unemployment at ages besides age 20. Separately for men and women, the table provides the correlation with the baseline distribution of cyclicality, the second-stage coefficient on median log wage, and the R-squared from the second-stage regression. Column (1) provides baseline specifications using all 38 majors; the coefficient on Median Log Wage is identical to the coefficient reported in Appendix Table A-8. Column (2) restricts the sample to those cohorts where valid measures of unemployment are available at both ages 10 and 30 (1960–2009 graduation years). Columns (3), (4), and (5) add major-specific controls for unemployment at age 10, age 30, and both unemployment rates, respectively.

Appendix - For Online Publication

A-1 Components of major categories

As discussed in the main paper, we aggregated individual majors from the ACS and B&B to create a set of 38 consistent major categories. The constituent components from each survey are listed in Table A-1.

Table A-1: Components of Major Categories Used in Analysis

Consistent Major Category	B&B components	ACS components
Accounting	Accounting	Accounting
Actuarial Science	N/A	Actuarial Science
Agriculture		
	Agriculture	
	Agricultural Science	
		General Agriculture
		Agriculture Production and Management
		Agricultural Economics
		Animal Sciences
		Food Science
		Plant Science and Agronomy
		Soil Science
		Miscellaneous Agriculture
Architecture	Architecture	Architecture
Biology Fields		
	Bio Sci: Botany	Botany
	Bio Sci: Zoology	Zoology
	Bio Sci: all other	
		Ecology
		Pharmacology
		Miscellaneous Biology
		Biology
		Molecular Biology
		Genetics
		Microbiology
		Physiology
	Interdisciplinary: Biopsychology	Cognitive Science and Biopsychology
		Neuroscience
Business Fields, not Finance		
	Business/Management Systems	Management Information Systems and Statistics
	Management/Business Administration	Business Management and Administration
	Marketing/Distribution	Marketing and Marketing Research
	Health: Health/Hospital Administration	Miscellaneous Business and Medical Administration
	Secretarial	
	Business Support	
		General Business
		Operations, Logistics and E-Commerce
		Business Economics
		Human Resources and Personnel Management
		International Business
		Hospitality Management
Chemistry and Pre-Med		
	Bio Sci: Biochemistry	Biochemical Sciences
	Physical Sci: Chemistry	Chemistry
		Health and Medical Preparatory Programs

The farthest left column lists the major category used for analysis in the paper. The second column lists the constituent fields of study identified in the ACS. The final column lists the constituent majors identified in the B&B. Original codes from the two datasets that appear to match exactly are listed in the same row.

Table A-1: Components of Major Categories Used in Analysis, con't

Consistent Major Category	B&B components	ACS components
Communications Fields		
	Communications	Communications
	Communication Technology	Communication Technologies
		Mass Media
		Advertising and Public Relations
Computer-Related Fields		
	Computer Programming	Computer Programming and Data Processing
	Computer and Information Sciences	
		Computer and Information Systems
		Computer Science
		Information Sciences
		Computer Information Management and Security
		Computer Networking and Telecommunications
Early and Elementary Education		
	Education: Elementary	Elementary Education
	Education: Early Childhood	Early Childhood Education
Economics	Economics	Economics
Education Fields, Other		
	Education: Physical	Physical and Health Education Teaching
	Education: Secondary	Secondary Teacher Education
	Education: Special	Special Needs Education
	Education: Other	Teacher Education: Multiple Levels
		Language and Drama Education
		General Education
		Educational Administration and Supervision
		School Student Counseling
		Mathematics Teacher Education
		Science and Computer Teacher Education
		Social Science or History Teacher Education
		Art and Music Education
		Miscellaneous Education
	Library/Archival Science	Library Science

The farthest left column lists the major category used for analysis in the paper. The second column lists the constituent fields of study identified in the ACS. The final column lists the constituent majors identified in the B&B. Original codes from the two datasets that appear to match exactly are listed in the same row.

Table A-1: Components of Major Categories Used in Analysis, con't

Consistent Major Category	B&B components	ACS components
Engineering Fields		
	Engineering: Chemical	Chemical Engineering
	Engineering: Civil	Civil Engineering
	Engineering: Electrical	Electrical Engineering
	Engineering: Mechanical	Mechanical Engineering
	Engineering: all other	
		General Engineering
		Aerospace Engineering
		Biological Engineering
		Architectural Engineering
		Computer Engineering
		Engineering Mechanics, Physics, and Science
		Environmental Engineering
		Geological and Geophysical Engineering
		Industrial and Manufacturing Engineering
		Materials Engineering and Materials Science
		Metallurgical Engineering
		Mining and Mineral Engineering
		Naval Architecture and Marine Engineering
		Nuclear Engineering
		Petroleum Engineering
		Miscellaneous Engineering
		Biomedical Engineering
Environmental and Natural Resource Fields		
	Forestry	Forestry
	Natural Resources	
	Interdisciplinary: Environmental Studies	
		Environment and Natural Resources
		Environmental Science
		Natural Resources Management
Family and Consumer Sciences		
		Family and Consumer Sciences
	Home Economics: all other	
	Vocational Home Econ: Child Care/Guidnce	
	Vocational Home Econ: Other	
	Textiles	
Finance	Finance	Finance
Industrial and Commerical Arts		
		Precision Production and Industrial Arts
	Precision Production	
	Industrial Arts: Construction	
	Industrial Arts: Electronics	
		Commercial Art and Graphic Design
	Commercial Art	
	Design	
Journalism	Journalism	Journalism

The farthest left column lists the major category used for analysis in the paper. The second column lists the constituent fields of study identified in the ACS. The final column lists the constituent majors identified in the B&B. Original codes from the two datasets that appear to match exactly are listed in the same row.

Table A-1: Components of Major Categories Used in Analysis, con't

Consistent Major Category	B&B components	ACS components
Leisure Studies		
	Leisure Studies	Physical Fitness, Parks, Recreation, and Leisure
	Health/Phys Ed/Recreation (HPER)	
Liberal Arts and History Fields		
	History	History
	Liberal Studies	
	Philosophy	
	Religious Studies	
	Clinical Pastoral Care	
		Liberal Arts and Humanities
		Liberal Arts
		Humanities
		Philosophy and Religious Studies
		Theology and Religious Vocations
		United States History
Literature and Languages Fields		
	Spanish	
	Foreign Langs: non-European	
	Foreign Langs: European, NOT Spanish	
		French, German, Latin and Other Common Foreign Language Studies
		Other Foreign Languages
		Linguistics and Foreign Languages
		Linguistics and Comparative Language and Literature
	Letters: English/American Lit.	
	Letters: Creative/Technical Writing	
	Letters: all other	
		English Language, Literature, and Composition
		English Language and Literature
		Composition and Speech
Mathematics and Statistics		
	Mathematics: NOT Statistics	Mathematics
	Mathematics: Statistics	Statistics and Decision Science
		Applied Mathematics
		Mathematics and Computer Science
Nursing	Health: Nursing	Nursing
Natural Science Fields, Other		
	Physical Sci: Earth Science	
		Geology and Earth Science
		Physical Sciences
		Atmospheric Sciences and Meteorology
		Geosciences
		Oceanography
	Interdisciplinary: Integrated/Gen. Sci.	Multi-disciplinary or General Science
	Physical Sci: NOT Chem/Physics/Earth	

The farthest left column lists the major category used for analysis in the paper. The second column lists the constituent fields of study identified in the ACS. The final column lists the constituent majors identified in the B&B. Original codes from the two datasets that appear to match exactly are listed in the same row.

Table A-1: Components of Major Categories Used in Analysis, con't

Consistent Major Category	B&B components	ACS components
Other Fields		
	Military Sciences	Military Technologies
	Interdisciplinary: all other	Interdisciplinary and Multi-Disciplinary Studies (General)
		Transportation Sciences and Technologies
	Transportation: Air	
	Transportation: Not Air	
	Basic/Personal Skills	
		Cosmetology Services and Culinary Arts
		Construction Services
		Electrical and Mechanic Repairs and Technologies
Political Science and International Relations		
	Political Science	Political Science and Government
	International Relations	International Relations
Pharmacy	N/A	Pharmacy, Pharmaceutical Sciences, and Administration
Physics		
	Physical Sci: Physics	
		Physics
		Astronomy and Astrophysics
Pre-Law and Legal Studies		
		Pre-Law and Legal Studies
		Court Reporting
	Law: Paralegal, includes pre-Law	
	Law	
Protective Services	Protective Services	Criminal Justice and Fire Protection
Psychology Fields		
	Psychology	Psychology
		Educational Psychology
		Clinical Psychology
		Counseling Psychology
		Industrial and Organizational Psychology
		Social Psychology
		Miscellaneous Psychology
Public Affairs, Health, Policy	Public Administration, NOT Social Work	Public Administration
		Public Policy
		Community and Public Health
	Health: Public Health	

The farthest left column lists the major category used for analysis in the paper. The second column lists the constituent fields of study identified in the ACS. The final column lists the constituent majors identified in the B&B. Original codes from the two datasets that appear to match exactly are listed in the same row.

Table A-1: Components of Major Categories Used in Analysis, con't

Consistent Major Category	B&B components	ACS components
Social Science Fields, Other		
		Area, Ethnic, and Civilization Studies
	American Civilization	
	Area Studies	
	African-American Studies	
	Ethnic Studies, NOT Black/Area Studies	
	Anthropology/Archaeology	Anthropology and Archeology
	Geography	Geography
	City Planning	
		Intercultural and International Studies
		Interdisciplinary Social Sciences
		General Social Sciences
		Criminology
		Miscellaneous Social Sciences
Social Work	Social Work	Social Work
		Human Services and Community Organization
Sociology	Sociology	Sociology
Technical Engineering Fields		
	Engineering Technology	Engineering Technologies
		Engineering and Industrial Management
		Electrical Engineering Technology
		Industrial Production Technologies
		Mechanical Engineering Related Technologies
		Miscellaneous Engineering Technologies
Technical Health Fields		
	Health: Dietetics	Nutrition Sciences
	Allied Health: Dental/Medical Tech	Medical Technologies Technicians
		Medical Assisting Services
	Allied Health: Community/Mental Health	
	Allied Health: General and Other	
	Health: Audiology	
	Health: Clinical Health Science	
	Health: Medicine	
	Health: all other	
		Nuclear, Industrial Radiology, and Biological Technologies
		General Medical and Health Services
		Health and Medical Administrative Services
		Miscellaneous Health Medical Professions
		Communication Disorders Sciences and Services
		Treatment Therapy Professions

The farthest left column lists the major category used for analysis in the paper. The second column lists the constituent fields of study identified in the ACS. The final column lists the constituent majors identified in the B&B. Original codes from the two datasets that appear to match exactly are listed in the same row.

Table A-1: Components of Major Categories Used in Analysis, con't

Consistent Major Category	B&B components	ACS components
Visual and Performing Arts		
	Art History/Fine Arts	
		Art History and Criticism
		Fine Arts
	Music	Music
	Speech/Drama	Drama and Theater Arts
	Film Arts	Film, Video and Photographic Arts
	Fine and Performing Arts: all other	Miscellaneous Fine Arts
		Studio Arts
		Visual and Performing Arts

The farthest left column lists the major category used for analysis in the paper. The second column lists the constituent fields of study identified in the ACS. The final column lists the constituent majors identified in the B&B. Original codes from the two datasets that appear to match exactly are listed in the same row.

A-2 Major-Specific Time Trends - Robustness

In this appendix section, we discuss the robustness of our choice of quadratic major-specific time trends in our empirical specification. The goal of the time trends is to capture structural shifts in both higher education and the labor market over our time period of more than 50 years. These shifts are by construction intended to be slower moving than that of the business cycle, as we attempt to isolate cyclical from structural fluctuations. In capturing these trends over time, we face a tradeoff between under-fitting and over-fitting the data. If we underfit the data, say with a linear trend, then we may attribute too much of the variation over time to cyclical fluctuations, whereas an extremely flexible trend will remove both slower moving and cyclical variation over time.

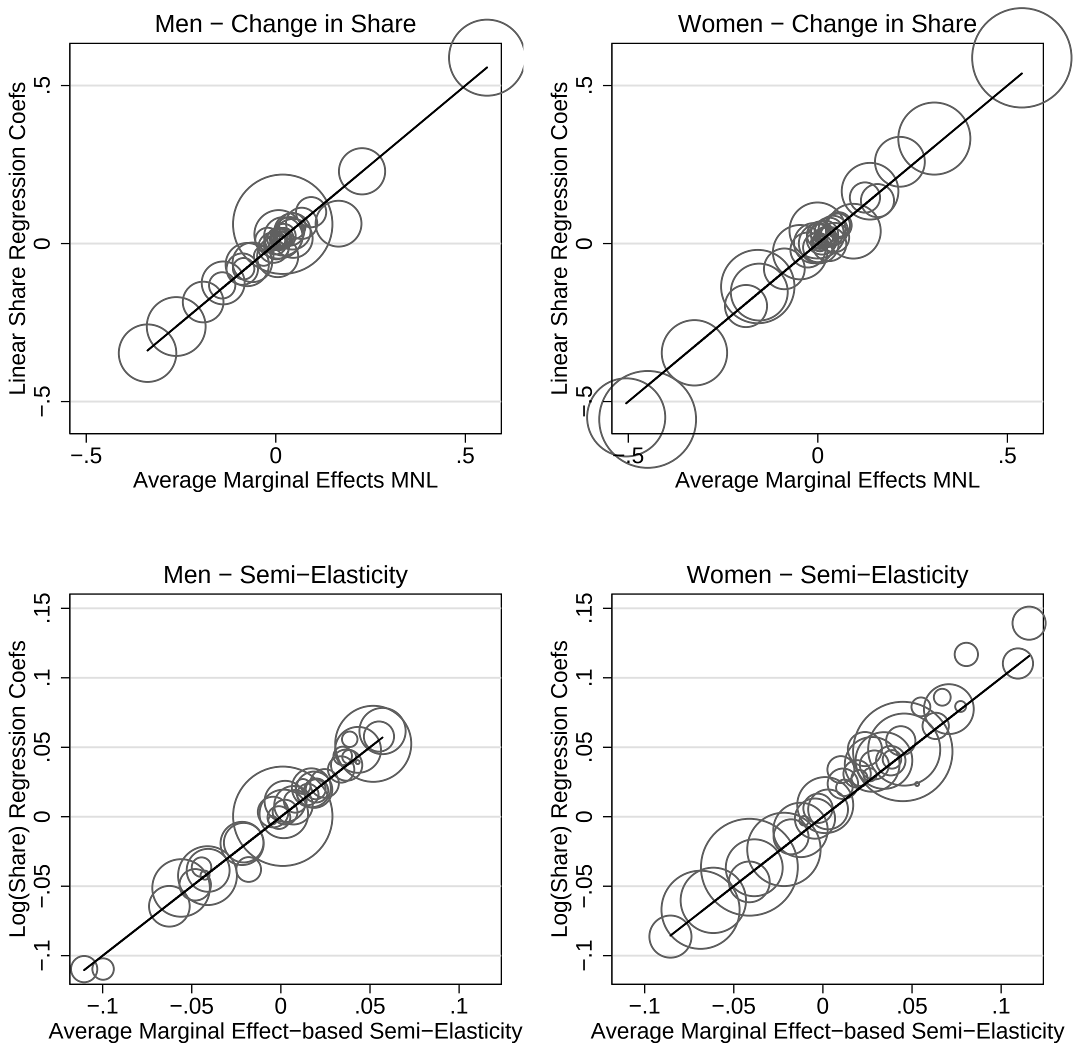
Our preferred specification, used throughout the paper, is to include a quadratic major-specific time trend in our estimates, as we show in the main text in Figure 2 for female engineering and early/elementary education majors. Appendix Figures A-3 and A-4 replicate this figure to present a sensitivity analysis of this choice of time trend, for women and men respectively.[42] The left panels of the figure show parametric alternatives, namely linear and cubic specifications. The linear option appears to dramatically underfit the trends in both cases, while the cubic looks quite similar to the quadratic specification. The right panels of Figure A-3 and A-4 show three non-parametric alternatives, with bandwidths of 5, 7, and 9 years, respectively, to isolate trends that are slower-moving than most business cycles. Not surprisingly, as the bandwidth is reduced, we observe a closer fit to the overall trend for both engineering and early/elementary education majors.

Appendix Table A-2 formalizes this sensitivity analysis across all 38 majors in both the log-share (panel A) and share (panel B) regressions. The sample is of women with bachelor's degrees, and the quadratic time trend is the baseline used in the main text. The explanatory power of each specification is shown in the first three columns, as measured by the percent of variance explained by trends alone. Each specification results in 38 estimates of r-squared (one for each major), and we report the 25th, 50th, and 75th percentiles of the resulting distribution of r-squareds. The linear parametric trend and the 9-year bandwidth non-parametric trend each perform relatively poorly (as seen in the figures discussed above), while the other specifications have broadly similar explanatory power. In the next column, we estimate the magnitude of overall sensitivity to the business cycle, as measured by the sum of the absolute value of share coefficients. The 5-year bandwidth appears to absorb a great deal of the business cycle fluctuation, while the other five specifications yield broadly similar total sensitivity measures. The final column presents the correlation of major-specific estimates of business cycle sensitivity with the baseline quadratic trends specification. Similar to the previous column, the correlation is relatively weaker for the 5-year nonparametric specification, but extremely strong across the other specifications. In sum, the comparisons in this figure and table suggest that our results are quite robust to a range of methods for

[42] Appendix Figures A-5 and A-6 provide the distributions of goodness-of-fit R^2 for women and men, respectively, with vertical lines to indicate the location of the four majors that we use as examples in the main text.

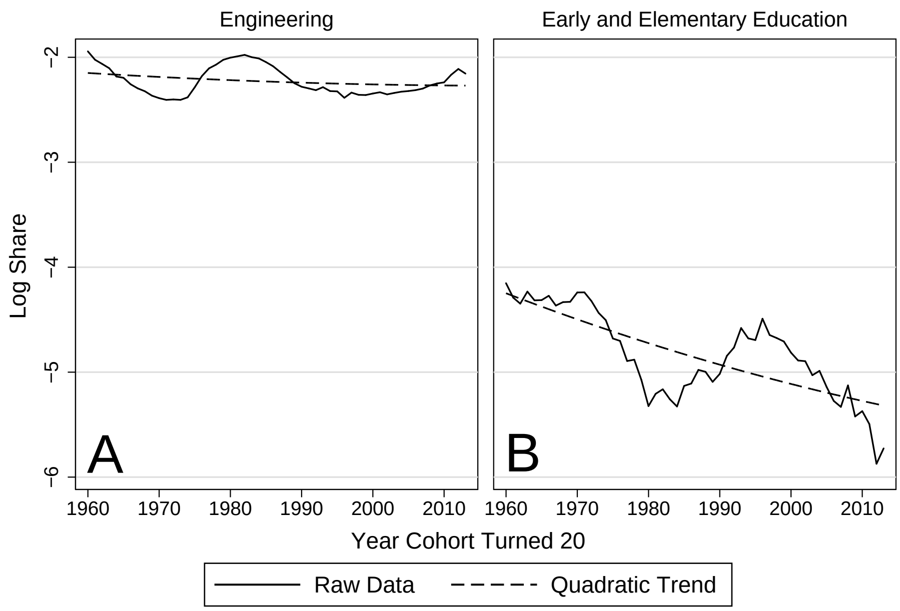
capturing long-term major-specific trends that are slower moving than the business cycle.

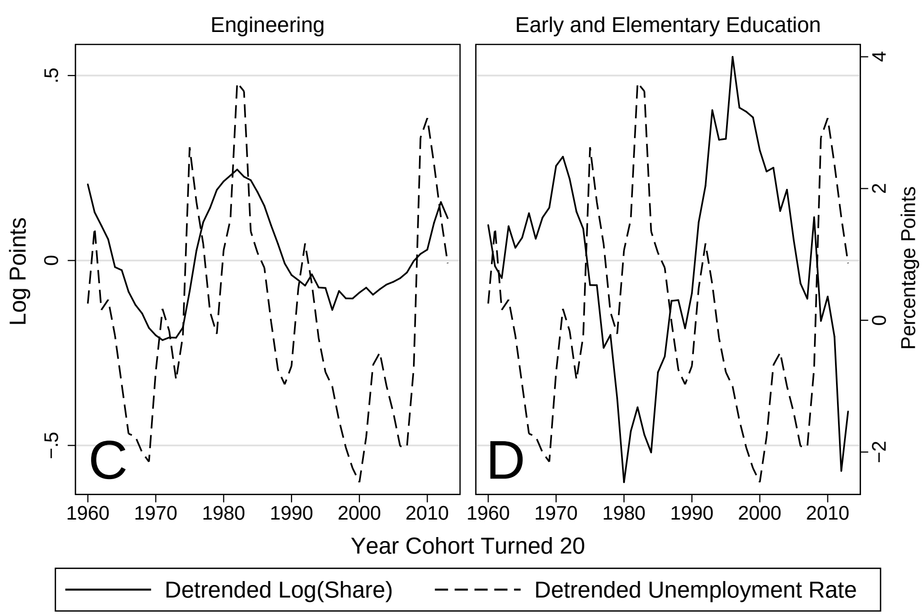
Figure A-1: Functional Form Comparison



Each figure shows the estimated change in share or the estimated percentage change in share of graduates selecting a given major due to a 1 percentage point increase in the unemployment rate. The reference lines are 45-degree lines based on the multinomial logit (MNL) based specifications. For the "Change in Share" estimates, the MNL-based estimates represent average marginal effects. For the "Change in Log(Share)" estimates, the MNL-based estimates represent average marginal semi-elasticities. Each circle represents one major category, and the relative size of the circle represents the relative long-run average share of graduates selecting that major. The one major category with a wide discrepancy is actuarial science in the Log(Share) specifications for women. This discrepancy is likely to the very small share of individuals selecting that major, and we omit this category for analysis based on the B&B because there is no corresponding major category in that dataset.

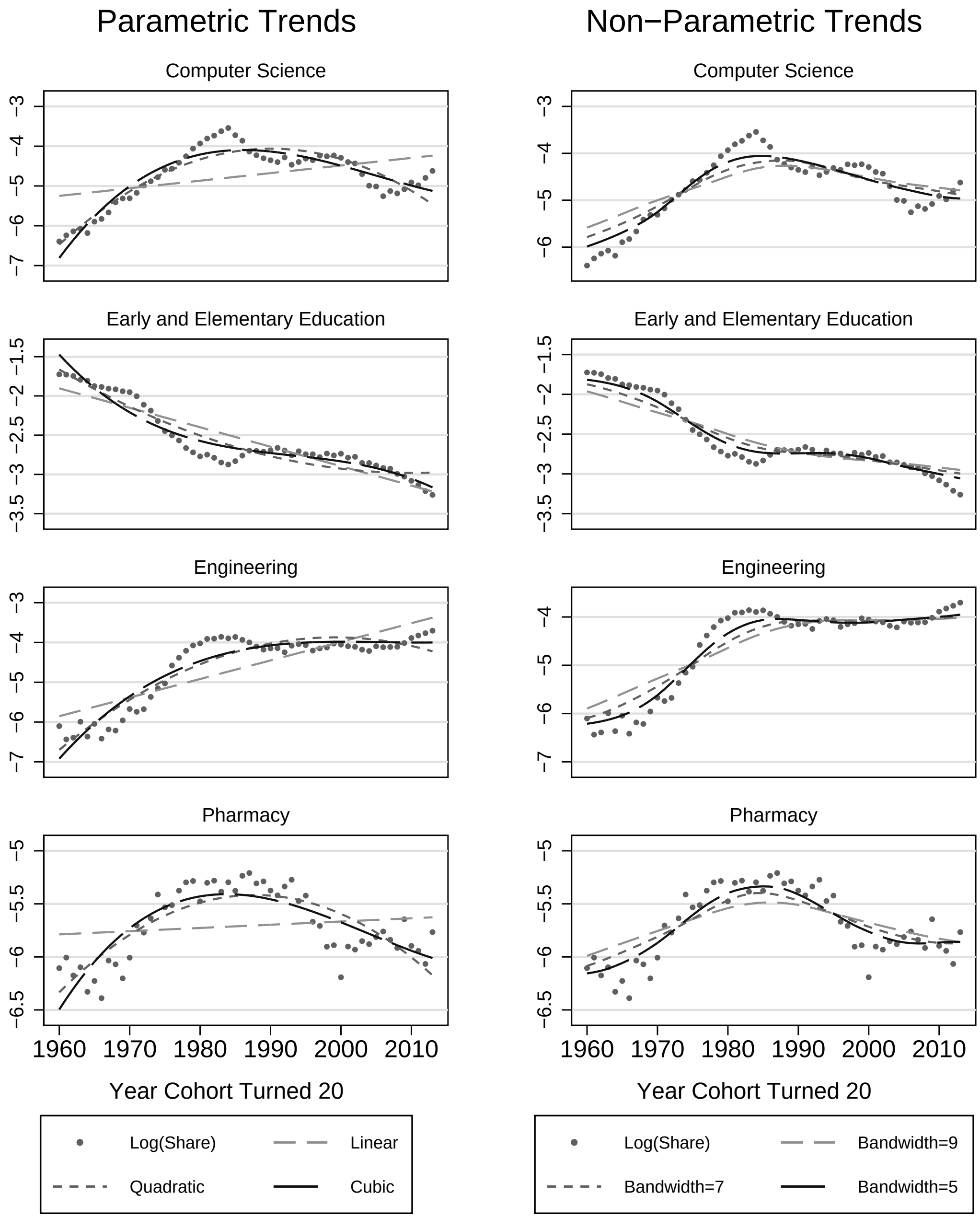
Figure A-2: Raw and Detrended Log-Shares of Cohort Selecting Major





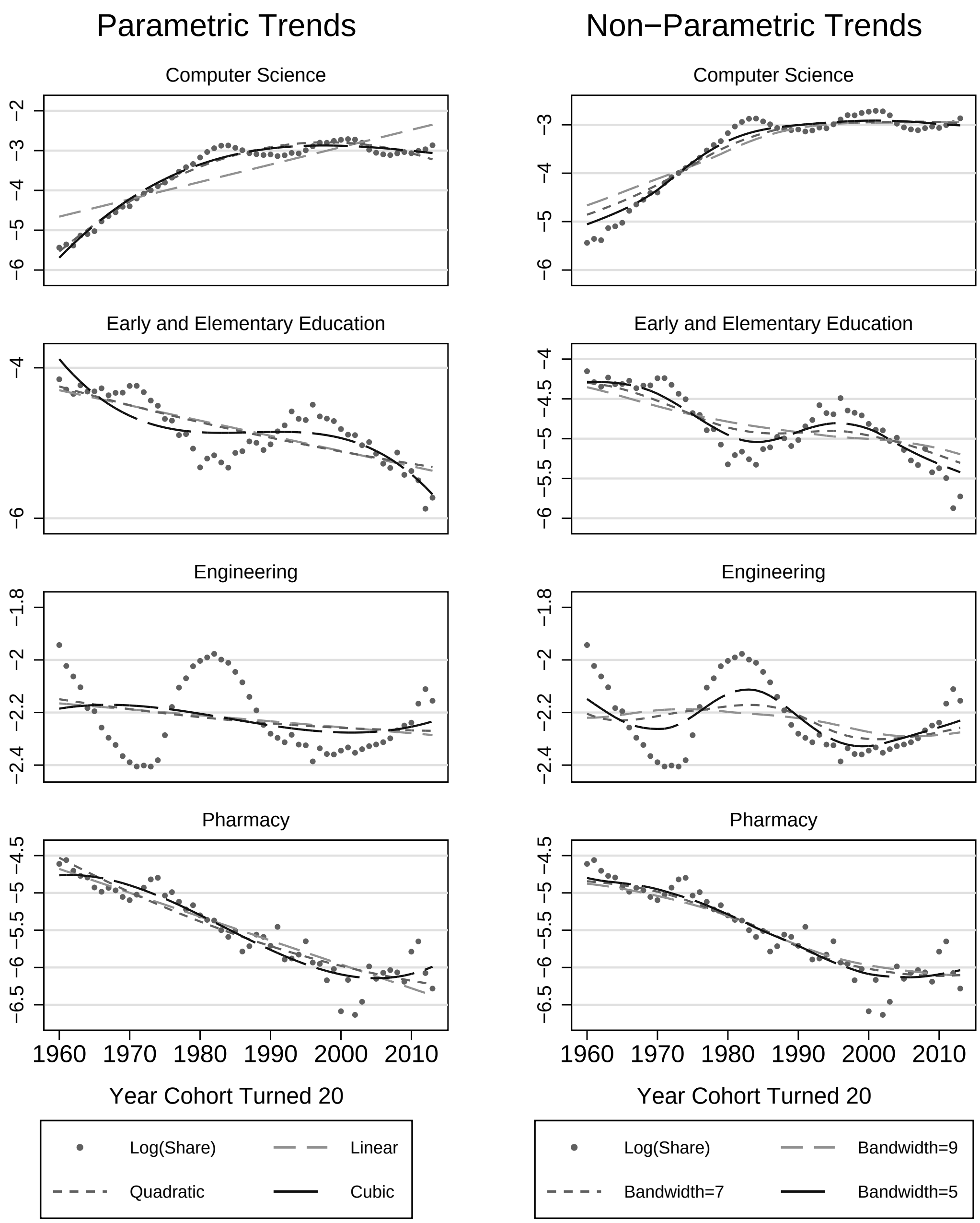
Data sources: BLS and authors' calculations from 2009–2018 ACS data. This analysis is based on the fields of study for birth cohorts of men who completed college degrees. Panels A and B show the raw data and best fit quadratic trends for the log(share) of graduates completing degrees in Engineering and Early and Elementary Education, respectively. Panels B and C show the time series of the residual log(share) variable after removing the trend as well as a similarly (quadratic) de-trended time series of the national unemployment rate.

Figure A-3: Major-Specific Time Trend Comparison – Women



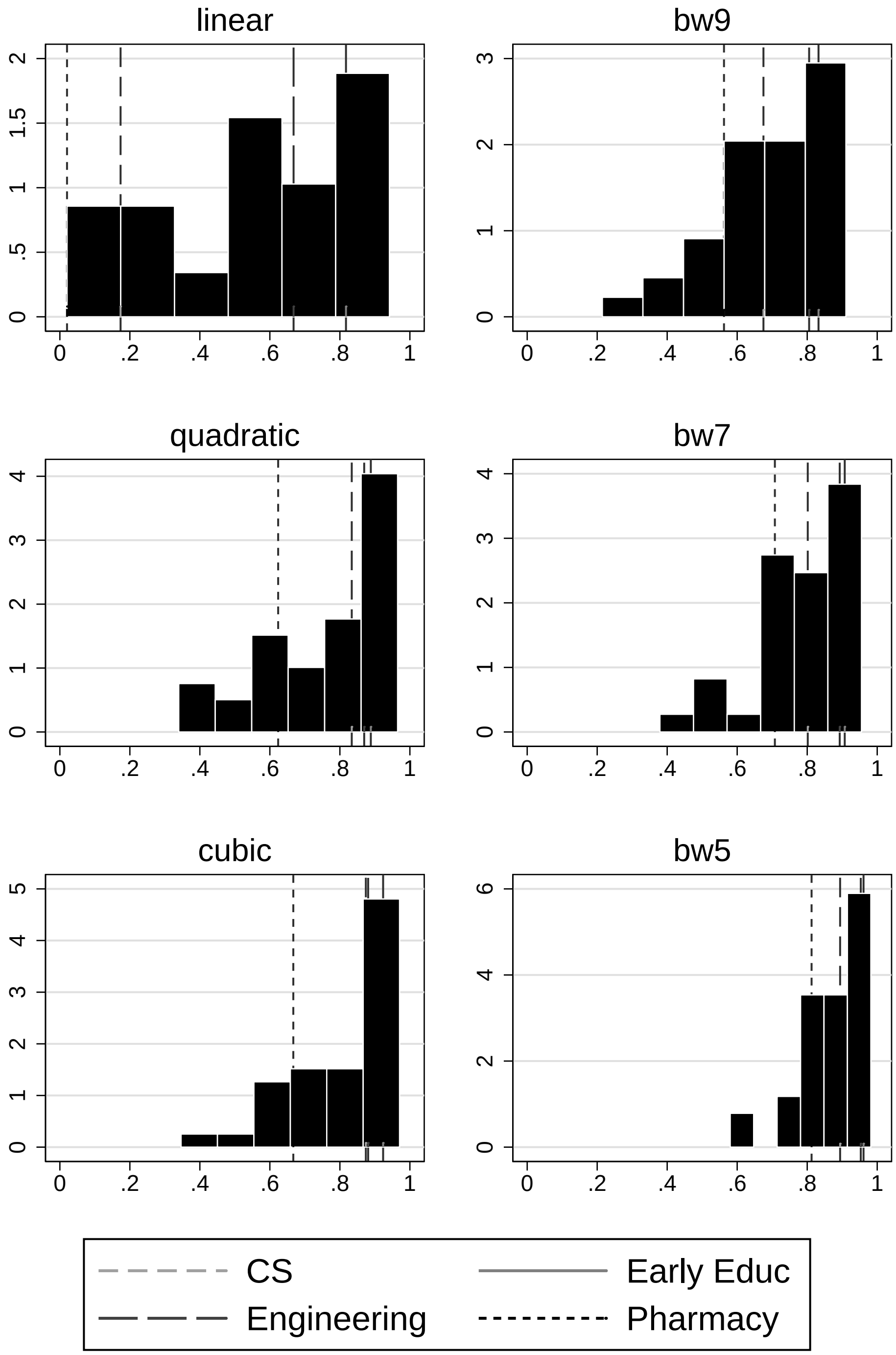
The eight panels present sensitivity analysis to specifying major-specific time trends parametrically (left four panels) or non-parametrically (right four panels). The sample is of women with bachelor's degrees, the quadratic time trend is the baseline used in the main text. The four majors, engineering, early/elementary education, pharmacy, and computer science, are chosen to replicate those presented in Figure 2.

Figure A-4: Major-Specific Time Trend Comparison – Men



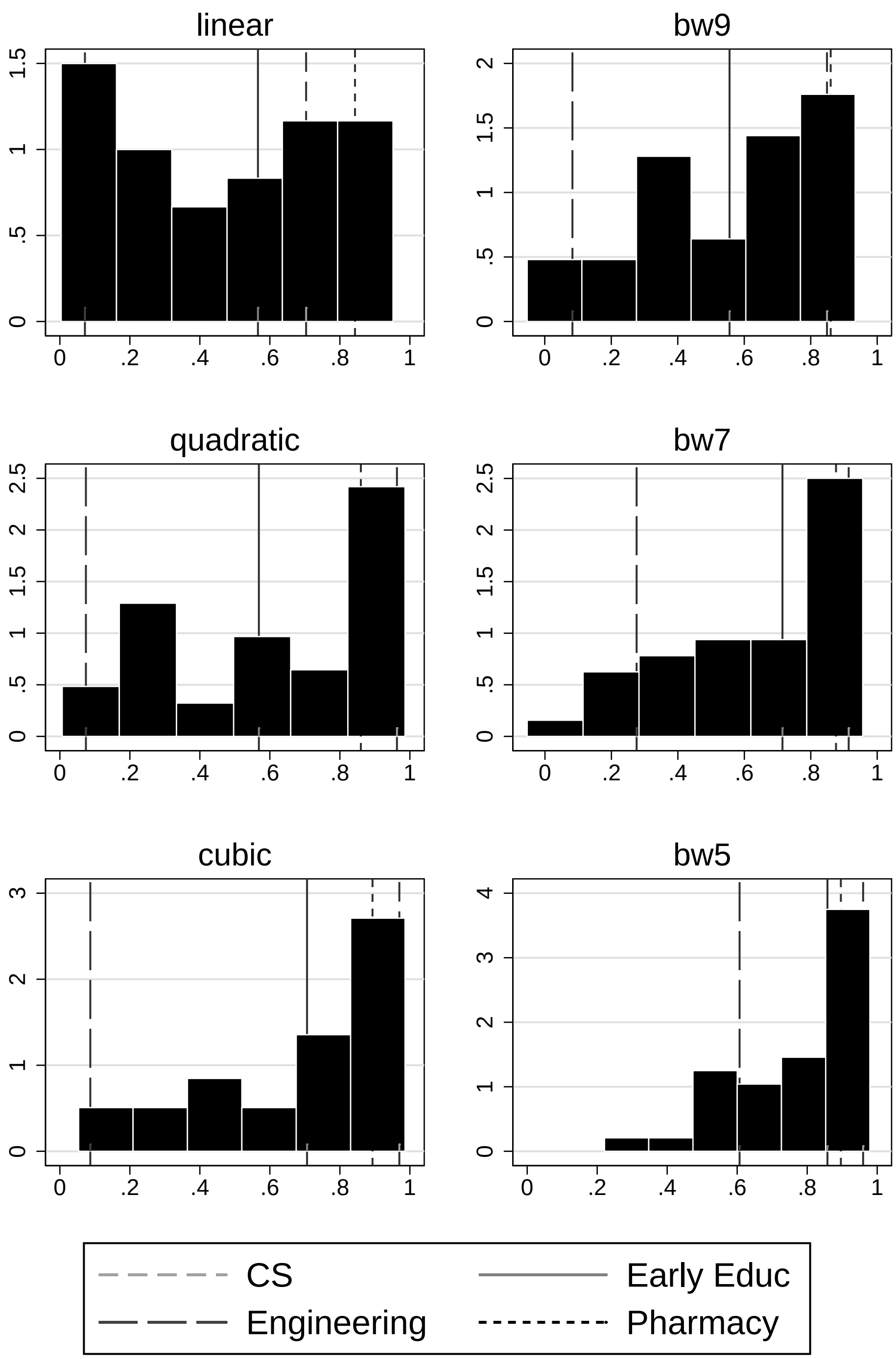
The eight panels present sensitivity analysis to specifying major-specific time trends parametrically (left four panels) or non-parametrically (right four panels). The sample is of men with bachelor's degrees, the quadratic time trend is the baseline used in the main text. The four majors, engineering, early/elementary education, pharmacy, and computer science, are chosen to replicate those presented in Figure 2.

Figure A-5: Major-Specific Time Trend Goodness-of-Fit Distributions – Women



The six panels present the distribution of R^2 from each major-specific time trend specification, estimated either parametrically (left three panels) or non-parametrically (right three panels). The sample is of women with bachelor's degrees, the quadratic time trend is the baseline used in the main text. Vertical lines are included for engineering, early/elementary education, pharmacy, and computer science to locate their values in each distribution.

Figure A-6: Major-Specific Time Trend Goodness-of-Fit Distributions – Men



The six panels present the distribution of R^2 from each major-specific time trend specification, estimated either parametrically (left three panels) or non-parametrically (right three panels). The sample is of men with bachelor's degrees, the quadratic time trend is the baseline used in the main text. Vertical lines are included for engineering, early/elementary education, pharmacy, and computer science to locate their values in each distribution.

Table A-2: Major-Specific Time Trend Comparison

	Percent of Variance Explained by Trends Alone			Sum of Absolute Value of Coefs	Correlation of Coefs w/ Quad Trends Version
	25th pct	50th pct	75th pct		
Panel A: Log(share) regressions					
Parametric					
linear	0.2952	0.5719	0.8147	–	0.9960
quadratic	0.6237	0.8429	0.8884	–	1
cubic	0.7008	0.8675	0.9210	–	0.9265
Non-parametric					
bw9	0.5815	0.7183	0.8323	–	0.9693
bw7	0.7048	0.8190	0.8926	–	0.9280
bw5	0.8125	0.8979	0.9425	–	0.7541
Panel B: Share regressions					
Parametric					
linear	0.3073	0.5676	0.8003	4.6414	0.9982
quadratic	0.6247	0.7730	0.8520	4.1640	1
cubic	0.6684	0.7983	0.8941	4.0319	0.9789
Non-parametric					
bw9	0.5916	0.7128	0.8288	4.0024	0.9834
bw7	0.6806	0.8116	0.8757	2.7829	0.9507
bw5	0.8093	0.8903	0.9305	1.6028	0.7276

The table presents sensitivity analysis to specifying major-specific time trends parametrically or non-parametrically in both the log-share (Panel A) and share (Panel B) regressions. The sample is of women with bachelor's degrees, and the quadratic time trend is the baseline used in the main text. The explanatory power of each specification is shown in the first three columns, as measured by the percent of variance explained by trends alone. Each specification results in 38 estimates of r-squared (one for each major), and we report the 25th, 50th, and 75th percentiles of the resulting distribution of r-squareds. In the next column, we estimate the magnitude of overall sensitivity to the business cycle, as measured by the sum of the absolute value of share coefficients. The final column presents the correlation of major-specific estimates of business cycle sensitivity with the baseline quadratic trends specification.

A-3 Coefficient Estimates for Major Cyclicality

For completeness, Table A-3 provides numerical coefficients and standard errors for the results displayed graphically in Figures 3–6 in the main text.

Table A-3: Complete Set of Coefficient Estimates for Equation 7

	Women					Men				
	Log(Share)		Share		Long-run Average Share	Log(Share)		Share		Long-run Average Share
Major	Coef.	Std. Error	Coef.	Std. Error	Mean	Coef.	Std. Error	Coef.	Std. Error	Mean
Accounting	0.0775***	(0.0087)	0.2587***	(0.0345)	0.0317	0.0617***	(0.0097)	0.2286***	(0.0347)	0.0398
Actuarial Science	0.0235	(0.0514)	0.0003	(0.0007)	0.0002	0.0393	(0.0526)	0.0022*	(0.0013)	0.0003
Agriculture	0.1168***	(0.0241)	0.0581***	(0.0132)	0.0070	0.0240**	(0.0096)	0.0388***	(0.0148)	0.0152
Architecture	0.0208	(0.0137)	0.0022	(0.0042)	0.0035	-0.0006	(0.0098)	0.0016	(0.0091)	0.0096
Biology Fields	0.0084	(0.0084)	0.0414	(0.0308)	0.0401	0.0020	(0.0135)	0.0291	(0.0606)	0.0439
Business Fields, not Finance	0.0470***	(0.0086)	0.5877***	(0.1335)	0.1262	0.0004	(0.0048)	0.0611	(0.0861)	0.1840
Chemistry and Pre-Med	0.0309***	(0.0085)	0.0300***	(0.0066)	0.0096	0.0372***	(0.0068)	0.0640***	(0.0131)	0.0182
Communications Fields	0.0377***	(0.0100)	0.0391	(0.0347)	0.0382	0.0111**	(0.0050)	-0.0412**	(0.0196)	0.0315
Computer-Related Fields	0.1103***	(0.0219)	0.1458***	(0.0358)	0.0117	0.0481***	(0.0132)	0.0630	(0.0764)	0.0393
Early and Elementary Education	-0.0670***	(0.0073)	-0.5501***	(0.0607)	0.0780	-0.1096***	(0.0180)	-0.0795***	(0.0123)	0.0086
Economics	0.0654***	(0.0122)	0.0577***	(0.0113)	0.0089	0.0083	(0.0086)	0.0227	(0.0236)	0.0276
Education Fields, Other	-0.0363***	(0.0069)	-0.5564***	(0.0859)	0.1199	-0.0513***	(0.0094)	-0.3468***	(0.0531)	0.0617
Engineering Fields	0.1393***	(0.0200)	0.1360***	(0.0256)	0.0140	0.0525***	(0.0087)	0.5882***	(0.1006)	0.1078
Environmental and Natural Resource Fields	0.0791***	(0.0297)	0.0212**	(0.0099)	0.0046	0.0111	(0.0210)	0.0147	(0.0202)	0.0096
Family and Consumer Sciences	-0.0144	(0.0088)	-0.0204	(0.0138)	0.0157	-0.0420***	(0.0144)	-0.0070***	(0.0025)	0.0015
Finance	0.0547***	(0.0173)	0.0191	(0.0194)	0.0110	0.0208*	(0.0116)	0.0164	(0.0339)	0.0281
Industrial and Commercial Arts	0.0238**	(0.0092)	0.0135	(0.0122)	0.0118	-0.0363***	(0.0126)	-0.0395***	(0.0096)	0.0071
Journalism	0.0403***	(0.0088)	0.0414***	(0.0088)	0.0111	0.0160	(0.0102)	0.0149*	(0.0086)	0.0085
Leisure Studies	0.0339**	(0.0140)	0.0273**	(0.0119)	0.0093	-0.0380**	(0.0170)	0.0109	(0.0172)	0.0114
Liberal Arts and History Fields	-0.0367***	(0.0057)	-0.1535***	(0.0233)	0.0414	-0.0424***	(0.0063)	-0.2626***	(0.0365)	0.0645
Literature and Languages Fields	-0.0602***	(0.0087)	-0.3457***	(0.0521)	0.0547	-0.0644***	(0.0098)	-0.1850***	(0.0280)	0.0308
Mathematics and Statistics	0.0060	(0.0111)	-0.0126	(0.0130)	0.0110	0.0034	(0.0081)	-0.0125	(0.0153)	0.0174
Natural Science Fields, Other	0.0373***	(0.0079)	0.0360***	(0.0081)	0.0108	0.0577***	(0.0075)	0.0994***	(0.0130)	0.0170
Nursing	0.0483***	(0.0081)	0.3322***	(0.0625)	0.0665	0.0438***	(0.0146)	0.0201**	(0.0081)	0.0064
Other Fields	0.0279**	(0.0134)	0.0009	(0.0027)	0.0033	0.0033	(0.0080)	-0.0108	(0.0115)	0.0114
Pharmacy	0.0860***	(0.0165)	0.0287***	(0.0053)	0.0036	0.0557***	(0.0183)	0.0150***	(0.0056)	0.0045
Physics	-0.0029	(0.0147)	-0.0005	(0.0017)	0.0011	0.0197**	(0.0088)	0.0146*	(0.0086)	0.0074
Political Science and International Relations	0.0053	(0.0077)	0.0002	(0.0153)	0.0203	-0.0192**	(0.0094)	-0.0665**	(0.0314)	0.0348
Pre-Law and Legal Studies	0.0302**	(0.0119)	0.0034	(0.0029)	0.0022	-0.0025	(0.0207)	0.0002	(0.0029)	0.0013
Protective Services	0.0487***	(0.0137)	-0.0016	(0.0124)	0.0149	0.0195*	(0.0116)	0.0385	(0.0286)	0.0245
Psychology Fields	-0.0235***	(0.0068)	-0.1361***	(0.0417)	0.0688	-0.0386***	(0.0124)	-0.1246***	(0.0408)	0.0343
Public Affairs, Health, Policy	0.0413***	(0.0099)	0.0211***	(0.0054)	0.0044	0.0431***	(0.0120)	0.0157***	(0.0045)	0.0036
Social Science Fields, Other	-0.0469***	(0.0119)	-0.0800***	(0.0219)	0.0212	-0.0490***	(0.0105)	-0.0809***	(0.0175)	0.0185
Social Work	-0.0013	(0.0100)	0.0013	(0.0203)	0.0206	0.0218	(0.0192)	0.0096	(0.0076)	0.0041
Sociology	-0.0863***	(0.0147)	-0.1978***	(0.0349)	0.0226	-0.1097***	(0.0178)	-0.1324***	(0.0216)	0.0129
Technical Engineering Fields	0.0794***	(0.0179)	0.0128***	(0.0029)	0.0015	0.0340***	(0.0090)	0.0550***	(0.0132)	0.0130
Technical Health Fields	0.0405***	(0.0087)	0.1657***	(0.0360)	0.0411	0.0189	(0.0117)	0.0243**	(0.0122)	0.0108
Visual and Performing Arts	-0.0095	(0.0086)	-0.0273	(0.0318)	0.0378	-0.0187**	(0.0088)	-0.0595**	(0.0235)	0.0291

This table provides a complete set of coefficient estimates and standard errors used to construct Figures 3–6 . Additional descriptions of the specification and data sources are available in the notes to those figures. "Long-Run Average" is the average (unweighted) share completing a given major using all 51 birth cohorts. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

A-4 Differences in Major Cyclicality by Gender

Table A-4 provides tests of the equality between genders of the Log(share) coefficients presented in Appendix Table A-3. Although there are several majors where the difference in semi-elasticity is statistically different from zero, these differences are typically differing magnitudes of coefficients in the same direction rather than differing signs.

Table A-4: Gender Differences in Major Cyclicality

	Men		Women		Difference		
	Coef.		Coef.		Coef.		S.E.
Accounting	0.0617	***	0.0775	***	0.0158	*	(0.0096)
Actuarial Science	0.0393		0.0235		-0.0158		(0.0810)
Agriculture	0.0240	**	0.1168	***	0.0928	***	(0.0185)
Architecture	-0.0006		0.0208		0.0214		(0.0132)
Biology Fields	0.0020		0.0084		0.0064		(0.0100)
Business Fields, not Finance	0.0004		0.0470	***	0.0466	***	(0.0057)
Chemistry and Pre-Med	0.0372	***	0.0309	***	-0.0063		(0.0085)
Communications Fields	0.0111	**	0.0377	***	0.0266	***	(0.0084)
Computer-Related Fields	0.0481	***	0.1103	***	0.0622	***	(0.0117)
Early and Elementary Education	-0.1096	***	-0.0670	***	0.0427	***	(0.0124)
Economics	0.0083		0.0654	***	0.0571	***	(0.0088)
Education Fields, Other	-0.0513	***	-0.0363	***	0.0149	***	(0.0050)
Engineering Fields	0.0525	***	0.1393	***	0.0868	***	(0.0134)
Environmental and Natural Resource Fields	0.0111		0.0791	***	0.0680	***	(0.0189)
Family and Consumer Sciences	-0.0420	***	-0.0144		0.0276	**	(0.0130)
Finance	0.0208	*	0.0547	***	0.0338	***	(0.0099)
Industrial and Commercial Arts	-0.0363	***	0.0238	**	0.0600	***	(0.0142)
Journalism	0.0160		0.0403	***	0.0243	***	(0.0073)
Leisure Studies	-0.0380	**	0.0339	**	0.0719	***	(0.0172)
Liberal Arts and History Fields	-0.0424	***	-0.0367	***	0.0057		(0.0042)
Literature and Languages Fields	-0.0644	***	-0.0602	***	0.0043		(0.0047)
Mathematics and Statistics	0.0034		0.0060		0.0027		(0.0081)
Natural Science Fields, Other	0.0577	***	0.0373	***	-0.0205	**	(0.0090)
Nursing	0.0438	***	0.0483	***	0.0045		(0.0112)
Other Fields	0.0033		0.0279	**	0.0246		(0.0158)
Pharmacy	0.0557	***	0.0860	***	0.0303		(0.0191)
Physics	0.0197	**	-0.0029		-0.0226	*	(0.0128)
Political Science and International Relations	-0.0192	**	0.0053		0.0245	**	(0.0113)
Pre-Law and Legal Studies	-0.0025		0.0302	**	0.0327		(0.0217)
Protective Services	0.0195	*	0.0487	***	0.0292	**	(0.0135)
Psychology Fields	-0.0386	***	-0.0235	***	0.0151	**	(0.0072)
Public Affairs, Health, Policy	0.0431	***	0.0413	***	-0.0018		(0.0092)
Social Science Fields, Other	-0.0490	***	-0.0469	***	0.0021		(0.0075)
Social Work	0.0218		-0.0013		-0.0231		(0.0155)
Sociology	-0.1097	***	-0.0863	***	0.0234	***	(0.0084)
Technical Engineering Fields	0.0340	***	0.0794	***	0.0453	***	(0.0154)
Technical Health Fields	0.0189		0.0405	***	0.0215	**	(0.0093)
Visual and Performing Arts	-0.0187	**	-0.0095		0.0092	*	(0.0050)

A-5 Cyclicality over Time

In this section, we provide results showing how the cyclicality of major choice changes over the time period we study. We fit regressions that allow the effects to be different for cohorts who turned 20 prior to and after 1980. Specifically, modify the main estimating equation to be:

$$y_{mc} = \beta_m^{pre} * \text{unemp\_20}_c + \beta_m^{post} * \text{unemp\_20}_c + \eta_m + \delta_{1m} * c + \delta_{2m} * c^2 + \epsilon_{mc}$$

Tables A-5 and A-6 provide the results of this estimation separately for men and women, respectively. The coefficients are quite similar across the two time periods, with correlation coefficients of 0.81 for men and 0.76. There are some statistically significant differences in major cyclicality across the two time periods, but in the majority of cases, the coefficients are in the same direction.

Table A-5: Comparison of Pre-1980 and Post-1980 Cyclicality Coefficients - Men

	Baseline			Pre-1980			Post-1980			Difference		
Major	Coef.		Std. Error	Coef.		Std. Error	Coef.		Std. Error	Coef.		Std. Error
Accounting	0.0617	***	(0.0093)	0.0684	***	(0.0108)	0.0628	***	(0.0094)	-0.0056		(0.0104)
Actuarial Science	0.0393		(0.0542)	-0.0057		(0.0462)	0.0513		(0.0599)	0.0570		(0.0414)
Agriculture	0.0240	**	(0.0091)	0.0482	***	(0.0104)	0.0215	**	(0.0094)	-0.0267	***	(0.0092)
Architecture	-0.0006		(0.0098)	0.0138		(0.0112)	-0.0011		(0.0080)	-0.0149	*	(0.0085)
Biology Fields	0.0020		(0.0129)	0.0326	**	(0.0131)	-0.0018		(0.0085)	-0.0345	***	(0.0111)
Business Fields, not Finance	0.0004		(0.0045)	-0.0134		(0.0093)	0.0058		(0.0053)	0.0192	*	(0.0105)
Chemistry and Pre-Med	0.0372	***	(0.0067)	0.0474	***	(0.0070)	0.0376	***	(0.0068)	-0.0098		(0.0080)
Communications Fields	0.0111	**	(0.0046)	0.0037		(0.0084)	0.0152	***	(0.0052)	0.0115		(0.0070)
Computer-Related Fields	0.0481	***	(0.0130)	0.0376	**	(0.0151)	0.0529	***	(0.0138)	0.0153		(0.0134)
Early and Elementary Education	-0.1096	***	(0.0173)	-0.1212	***	(0.0273)	-0.1047	***	(0.0175)	0.0165		(0.0225)
Economics	0.0083		(0.0083)	-0.0282	**	(0.0113)	0.0184	**	(0.0077)	0.0466	***	(0.0117)
Education Fields, Other	-0.0513	***	(0.0091)	-0.0584	***	(0.0134)	-0.0472	***	(0.0087)	0.0112		(0.0114)
Engineering Fields	0.0525	***	(0.0084)	0.0296	*	(0.0148)	0.0598	***	(0.0085)	0.0302	**	(0.0148)
Environmental and Natural Resource Fields	0.0111		(0.0200)	0.0673	***	(0.0167)	0.0019		(0.0132)	-0.0654	***	(0.0149)
Family and Consumer Sciences	-0.0420	***	(0.0142)	-0.0398	**	(0.0158)	-0.0399	***	(0.0142)	-0.0001		(0.0120)
Finance	0.0208	*	(0.0109)	-0.0198		(0.0156)	0.0319	***	(0.0106)	0.0517	***	(0.0150)
Industrial and Commerical Arts	-0.0363	***	(0.0117)	-0.0669	***	(0.0181)	-0.0273	**	(0.0122)	0.0396	***	(0.0129)
Journalism	0.0160		(0.0101)	0.0337	***	(0.0108)	0.0149		(0.0096)	-0.0189	*	(0.0097)
Leisure Studies	-0.0380	**	(0.0163)	-0.0091		(0.0177)	-0.0415	***	(0.0122)	-0.0323	*	(0.0164)
Liberal Arts and History Fields	-0.0424	***	(0.0058)	-0.0585	***	(0.0107)	-0.0365	***	(0.0060)	0.0221	**	(0.0096)
Literature and Languages Fields	-0.0644	***	(0.0092)	-0.1062	***	(0.0144)	-0.0531	***	(0.0116)	0.0531	***	(0.0140)
Mathematics and Statistics	0.0034		(0.0078)	-0.0333	***	(0.0066)	0.0136	**	(0.0055)	0.0469	***	(0.0079)
Natural Science Fields, Other	0.0577	***	(0.0071)	0.0775	***	(0.0083)	0.0562	***	(0.0070)	-0.0213	**	(0.0084)
Nursing	0.0438	***	(0.0142)	0.0748	***	(0.0149)	0.0399	***	(0.0102)	-0.0349	***	(0.0114)
Other Fields	0.0033		(0.0074)	-0.0105		(0.0113)	0.0087		(0.0081)	0.0192	*	(0.0113)
Pharmacy	0.0557	***	(0.0179)	0.0710	***	(0.0164)	0.0551	***	(0.0176)	-0.0159	*	(0.0094)
Physics	0.0197	**	(0.0085)	-0.0087		(0.0110)	0.0282	***	(0.0084)	0.0369	***	(0.0088)
Political Science and International Relations	-0.0192	**	(0.0091)	-0.0327	**	(0.0124)	-0.0138		(0.0094)	0.0189	*	(0.0108)
Pre-Law and Legal Studies	-0.0025		(0.0204)	-0.0396	*	(0.0223)	0.0079		(0.0225)	0.0474	***	(0.0164)
Protective Services	0.0195	*	(0.0113)	0.0178		(0.0127)	0.0224	**	(0.0111)	0.0046		(0.0123)
Psychology Fields	-0.0386	***	(0.0120)	-0.0365	**	(0.0152)	-0.0365	***	(0.0108)	0.0000		(0.0137)
Public Affairs, Health, Policy	0.0431	***	(0.0115)	0.0529	***	(0.0112)	0.0436	***	(0.0114)	-0.0093		(0.0109)
Social Science Fields, Other	-0.0490	***	(0.0101)	-0.0503	***	(0.0149)	-0.0461	***	(0.0092)	0.0042		(0.0137)
Social Work	0.0218		(0.0182)	0.0482	**	(0.0184)	0.0188		(0.0170)	-0.0294	***	(0.0098)
Sociology	-0.1097	***	(0.0173)	-0.1137	***	(0.0206)	-0.1063	***	(0.0173)	0.0074		(0.0181)
Technical Engineering Fields	0.0340	***	(0.0088)	0.0153		(0.0114)	0.0405	***	(0.0083)	0.0252	**	(0.0114)
Technical Health Fields	0.0189	*	(0.0109)	0.0266	**	(0.0115)	0.0199	**	(0.0095)	-0.0068		(0.0090)
Visual and Performing Arts	-0.0187	**	(0.0086)	0.0033		(0.0103)	-0.0207	***	(0.0056)	-0.0240	***	(0.0086)

Note: Column (1) represents the baseline national coefficients using the 1960–2013 sample. Column (2) represents the coefficients on the pre-1980 subsample, while Column (3) shows the coefficients on the post-1980 subsample. Column (4) reports the difference between the pre-1980 and post-1980 coefficients. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A-6: Comparison of Pre-1980 and Post-1980 Cyclicality Coefficients - Women

	Baseline			Pre-1980			Post-1980			Difference		
Major	Coef.		Std. Error	Coef.		Std. Error	Coef.		Std. Error	Coef.		Std. Error
Accounting	0.0775	***	(0.0082)	0.0713	***	(0.0125)	0.0794	***	(0.0087)	0.0081		(0.0110)
Actuarial Science	0.0235		(0.0493)	0.0355		(0.0782)	0.0247		(0.0486)	-0.0108		(0.0584)
Agriculture	0.1168	***	(0.0231)	0.2269	***	(0.0175)	0.0944	***	(0.0186)	-0.1325	***	(0.0179)
Architecture	0.0208		(0.0132)	0.0745	***	(0.0141)	0.0102		(0.0150)	-0.0643	***	(0.0119)
Biology Fields	0.0084		(0.0082)	0.0367	***	(0.0090)	0.0031		(0.0051)	-0.0336	***	(0.0084)
Business Fields, not Finance	0.0470	***	(0.0082)	0.0367	***	(0.0119)	0.0497	***	(0.0082)	0.0131		(0.0115)
Chemistry and Pre-Med	0.0309	***	(0.0081)	0.0380	***	(0.0101)	0.0300	***	(0.0084)	-0.0080		(0.0086)
Communications Fields	0.0377	***	(0.0096)	0.0186		(0.0117)	0.0423	***	(0.0090)	0.0238	**	(0.0103)
Computer-Related Fields	0.1103	***	(0.0207)	0.1031	***	(0.0230)	0.1124	***	(0.0215)	0.0093		(0.0178)
Early and Elementary Education	-0.0670	***	(0.0069)	-0.0790	***	(0.0133)	-0.0638	***	(0.0078)	0.0152		(0.0138)
Economics	0.0654	***	(0.0116)	0.0487	***	(0.0142)	0.0695	***	(0.0122)	0.0208		(0.0137)
Education Fields, Other	-0.0363	***	(0.0066)	-0.0279	**	(0.0115)	-0.0375	***	(0.0059)	-0.0096		(0.0119)
Engineering Fields	0.1393	***	(0.0191)	0.1420	***	(0.0326)	0.1394	***	(0.0192)	-0.0026		(0.0263)
Environmental and Natural Resource Fields	0.0791	***	(0.0283)	0.1978	***	(0.0213)	0.0549	**	(0.0219)	-0.1429	***	(0.0189)
Family and Consumer Sciences	-0.0144	*	(0.0085)	0.0226	**	(0.0098)	-0.0216	***	(0.0067)	-0.0442	***	(0.0101)
Finance	0.0547	***	(0.0160)	0.0228		(0.0211)	0.0619	***	(0.0153)	0.0392	**	(0.0179)
Industrial and Commerical Arts	0.0238	***	(0.0088)	0.0357	***	(0.0094)	0.0219	**	(0.0107)	-0.0138		(0.0088)
Journalism	0.0403	***	(0.0085)	0.0575	***	(0.0082)	0.0374	***	(0.0096)	-0.0201	**	(0.0078)
Leisure Studies	0.0339	**	(0.0135)	0.0986	***	(0.0120)	0.0210	*	(0.0112)	-0.0776	***	(0.0121)
Liberal Arts and History Fields	-0.0367	***	(0.0053)	-0.0461	***	(0.0089)	-0.0341	***	(0.0057)	0.0120		(0.0092)
Literature and Languages Fields	-0.0602	***	(0.0083)	-0.0945	***	(0.0123)	-0.0524	***	(0.0092)	0.0421	***	(0.0134)
Mathematics and Statistics	0.0060		(0.0106)	-0.0276	**	(0.0121)	0.0137		(0.0106)	0.0413	***	(0.0122)
Natural Science Fields, Other	0.0373	***	(0.0077)	0.0524	***	(0.0094)	0.0347	***	(0.0073)	-0.0176	**	(0.0081)
Nursing	0.0483	***	(0.0079)	0.0794	***	(0.0058)	0.0424	***	(0.0063)	-0.0370	***	(0.0067)
Other Fields	0.0279	**	(0.0128)	0.0585	***	(0.0145)	0.0221	**	(0.0109)	-0.0364	**	(0.0142)
Pharmacy	0.0860	***	(0.0159)	0.0893	***	(0.0187)	0.0859	***	(0.0160)	-0.0034		(0.0120)
Physics	-0.0029		(0.0140)	-0.0251		(0.0187)	0.0024		(0.0130)	0.0275	**	(0.0133)
Political Science and International Relations	0.0053		(0.0072)	-0.0177	*	(0.0103)	0.0107		(0.0079)	0.0284	***	(0.0096)
Pre-Law and Legal Studies	0.0302	***	(0.0107)	0.0089		(0.0132)	0.0353	***	(0.0124)	0.0264	**	(0.0119)
Protective Services	0.0487	***	(0.0132)	0.0781	***	(0.0139)	0.0431	***	(0.0107)	-0.0350	***	(0.0094)
Psychology Fields	-0.0235	***	(0.0066)	-0.0222	**	(0.0105)	-0.0232	***	(0.0068)	-0.0010		(0.0116)
Public Affairs, Health, Policy	0.0413	***	(0.0091)	0.0692	***	(0.0118)	0.0361	***	(0.0081)	-0.0331	***	(0.0099)
Social Science Fields, Other	-0.0469	***	(0.0116)	-0.0279	*	(0.0161)	-0.0502	***	(0.0097)	-0.0223		(0.0138)
Social Work	-0.0013		(0.0094)	0.0331	***	(0.0090)	-0.0079		(0.0068)	-0.0410	***	(0.0080)
Sociology	-0.0863	***	(0.0141)	-0.0744	***	(0.0212)	-0.0881	***	(0.0134)	-0.0137		(0.0193)
Technical Engineering Fields	0.0794	***	(0.0164)	0.1005	***	(0.0252)	0.0756	***	(0.0184)	-0.0249		(0.0210)
Technical Health Fields	0.0405	***	(0.0083)	0.0760	***	(0.0076)	0.0337	***	(0.0054)	-0.0423	***	(0.0074)
Visual and Performing Arts	-0.0095		(0.0083)	0.0248	***	(0.0092)	-0.0161	**	(0.0067)	-0.0409	***	(0.0097)

Note: Column (1) represents the baseline national coefficients using the 1960–2013 sample. Column (2) represents the coefficients on the pre-1980 subsample, while Column (3) shows the coefficients on the post-1980 subsample. Column (4) reports the difference between the pre-1980 and post-1980 coefficients. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

A-6 Effects Similar Throughout Cycle

Tables A-7 and A-8 examine whether majors' cyclical responses are similar throughout a business cycle for the sample of women and the sample of men, respectively. In each table, the first column reproduces the baseline estimate. The second and third columns present the semi-elasticity of the major's share with respect to the unemployment rate for periods when the unemployment rate fell from the year prior and rose compared to the year prior, respectively. The fourth column provides the difference in these coefficients. Finally, the table includes the relationship between these estimated semi-elasticities and the log of the median mid-career earnings, i.e. a coefficient estimate similar to Figure 7 in the main paper. The results reveal quantitatively small and typically statistically insignificant differences, suggesting that students respond similar to the level of unemployment rate regardless of whether it recently rose or fell.

Table A-7: Similar Responses During Times of Rising and Falling Unemployment - Women

	(1)	(2)	(3)	(4)
Accounting	0.0775 ***	0.0938 ***	0.0770 ***	-0.0168
Actuarial Science	0.0235	0.0507	-0.0019	-0.0526
Agriculture	0.1168 ***	0.1297 ***	0.0999 ***	-0.0298
Architecture	0.0208	0.0174	0.0243	0.0069
Biology Fields	0.0084	0.0104	0.0096	-0.0008
Business Fields, not Finance	0.0470 ***	0.0558 ***	0.0470 ***	-0.0088
Chemistry and Pre-Med	0.0309 ***	0.0366 ***	0.0334 ***	-0.0032
Communications Fields	0.0377 ***	0.0469 ***	0.0261	-0.0208
Computer-Related Fields	0.1103 ***	0.1406 ***	0.0948 ***	-0.0458
Early and Elementary Education	-0.0670 ***	-0.0824 ***	-0.0643 ***	0.0181
Economics	0.0654 ***	0.0804 ***	0.0686 ***	-0.0118
Education Fields, Other	-0.0363 ***	-0.0439 ***	-0.0387 ***	0.0052
Engineering Fields	0.1393 ***	0.1830 ***	0.1068 ***	-0.0762 **
Environmental and Natural Resource Fields	0.0791 ***	0.0803 *	0.0823 *	0.0020
Family and Consumer Sciences	-0.0144 *	-0.0181	-0.0166	0.0015
Finance	0.0547 ***	0.0691 ***	0.0383	-0.0308
Industrial and Commercial Arts	0.0238 ***	0.0206 *	0.0157	-0.0049
Journalism	0.0403 ***	0.0509 ***	0.0338 **	-0.0171
Leisure Studies	0.0339 **	0.0381 *	0.0251	-0.0130
Liberal Arts and History Fields	-0.0367 ***	-0.0460 ***	-0.0318 ***	0.0142
Literature and Languages Fields	-0.0602 ***	-0.0724 ***	-0.0523 ***	0.0201
Mathematics and Statistics	0.0060	0.0177	0.0040	-0.0137
Natural Science Fields, Other	0.0373 ***	0.0479 ***	0.0338 **	-0.0141
Nursing	0.0483 ***	0.0520 ***	0.0477 ***	-0.0043
Other Fields	0.0279 **	0.0111	0.0501 **	0.0390
Pharmacy	0.0860 ***	0.1002 ***	0.0726 ***	-0.0276
Physics	-0.0029	0.0083	-0.0306	-0.0389
Political Science and International Relations	0.0053	0.0054	0.0019	-0.0035
Pre-Law and Legal Studies	0.0302 ***	0.0436 ***	0.0037	-0.0399
Protective Services	0.0487 ***	0.0622 ***	0.0244	-0.0378
Psychology Fields	-0.0235 ***	-0.0267 ***	-0.0261 **	0.0006
Public Affairs, Health, Policy	0.0413 ***	0.0474 ***	0.0436 ***	-0.0038
Social Science Fields, Other	-0.0469 ***	-0.0622 ***	-0.0353 *	0.0269
Social Work	-0.0013	0.0010	0	-0.0010
Sociology	-0.0863 ***	-0.1077 ***	-0.0712 ***	0.0365
Technical Engineering Fields	0.0794 ***	0.0920 ***	0.1088 ***	0.0168
Technical Health Fields	0.0405 ***	0.0454 ***	0.0414 ***	-0.0040
Visual and Performing Arts	-0.0095	-0.0203 **	-0.0046	0.0157
Coefficients on Median Log Wage	0.1464 ***	0.1840 ***	0.1409 ***	-0.0431 ***
p-value of F-test				0.0000

Note: Column (1) represents the baseline coefficients for women as presented in Table A-3 of the main paper. Columns (2)–(4) provide the results of an interaction model that allows the impact of the unemployment rate to be different in years when the unemployment rate is rising (column 2) or falling (column 3). Column (4) provides the difference in these estimates. Although few individual majors have statistically significant differences, the test of the joint null that all differences are zero is rejected ($p < 0.001$). For each set of cohorts, however, the relationship between the elasticities and the long-run earnings of the major are very similar. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A-8: Similar Responses During Times of Rising and Falling Unemployment - Men

	(1)		(2)		(3)		(4)	
Accounting	0.0617	***	0.0639	***	0.0685	***	0.0046	
Actuarial Science	0.0393		-0.0358		0.1635	**	0.1993	**
Agriculture	0.0240	**	0.0232	*	0.0372	***	0.0140	
Architecture	-0.0006		-0.0127		0.0070		0.0197	
Biology Fields	0.0020		0.0025		0.0065		0.0040	
Business Fields, not Finance	0.0004		-0.0014		0.0060		0.0074	
Chemistry and Pre-Med	0.0372	***	0.0325	***	0.0533	***	0.0208	
Communications Fields	0.0111	**	0.0168	**	0.0020		-0.0148	
Computer-Related Fields	0.0481	***	0.0627	***	0.0341		-0.0286	
Early and Elementary Education	-0.1096	***	-0.1315	***	-0.1048	***	0.0267	
Economics	0.0083		0.0110		0.0094		-0.0016	
Education Fields, Other	-0.0513	***	-0.0677	***	-0.0401	**	0.0276	
Engineering Fields	0.0525	***	0.0661	***	0.0501	***	-0.0160	
Environmental and Natural Resource Fields	0.0111		0.0129		0.0008		-0.0121	
Family and Consumer Sciences	-0.0420	***	-0.0553	***	-0.0395	*	0.0158	
Finance	0.0208	*	0.0296		0.0240		-0.0056	
Industrial and Commercial Arts	-0.0363	***	-0.0549	***	-0.0179		0.0370	
Journalism	0.0160		0.0133		0.0173		0.0040	
Leisure Studies	-0.0380	**	-0.0381	*	-0.0517		-0.0136	
Liberal Arts and History Fields	-0.0424	***	-0.0506	***	-0.0452	***	0.0054	
Literature and Languages Fields	-0.0644	***	-0.0787	***	-0.0583	***	0.0204	
Mathematics and Statistics	0.0034		0.0087		0.0001		-0.0086	
Natural Science Fields, Other	0.0577	***	0.0522	***	0.0659	***	0.0137	
Nursing	0.0438	***	0.0438	**	0.0440		0.0002	
Other Fields	0.0033		-0.0095		0.0227	*	0.0322	*
Pharmacy	0.0557	***	0.0612	**	0.0652	**	0.0040	
Physics	0.0197	**	0.0227	**	0.0146		-0.0081	
Political Science and International Relations	-0.0192	**	-0.0255	**	-0.0254	**	0.0001	
Pre-Law and Legal Studies	-0.0025		0.0130		-0.0166		-0.0296	
Protective Services	0.0195	*	0.0288	*	0.0136		-0.0152	
Psychology Fields	-0.0386	***	-0.0399	**	-0.0512	**	-0.0113	
Public Affairs, Health, Policy	0.0431	***	0.0537	***	0.0195		-0.0342	
Social Science Fields, Other	-0.0490	***	-0.0502	***	-0.0610	***	-0.0108	
Social Work	0.0218		0.0278		0.0104		-0.0174	
Sociology	-0.1097	***	-0.1347	***	-0.1133	***	0.0214	
Technical Engineering Fields	0.0340	***	0.0427	***	0.0333	*	-0.0094	
Technical Health Fields	0.0189	*	0.0219		0.0289		0.0070	
Visual and Performing Arts	-0.0187	**	-0.0258	**	-0.0231		0.0027	
Coefficients on Median Log Wage	0.1231	***	0.1442	***	0.1331	***	-0.0111	
p-value of F-test							0.0000	

Note: Column (1) represents the baseline coefficients for men as presented in Table A-3 of the main paper. Columns (2)–(4) provide the results of an interaction model that allows the impact of the unemployment rate to be different in years when the unemployment rate is rising (column 2) or falling (column 3). Column (4) provides the difference in these estimates. Although few individual majors have statistically significant differences, the test of the joint null that all differences are zero is rejected ($p < 0.001$). For each set of cohorts, however, the relationship between the elasticities and the long-run earnings of the major are very similar. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

A-7 Descriptive statistics for correlates of major cyclicality and bivariate relationships with unemployment

Table A-9 provides descriptives statistics for the major-specific characteristics used in the analysis in section 4 of the main paper. The first two rows of each panel summarize the major-specific coefficients on the unemployment rate estimated based on Equation 7. The number of observations varies in B&B variables due to disclosure requirements. Calculations that would risk confidentiality were not provided by the online data extraction tool.

Table A-10 presents results from a series of bivariate regressions using the semi-elasticity coefficients on the unemployment rate from Equation (7) as the dependent variable and a number of major characteristics as explanatory variables:

$$\hat{\beta}_m = \phi_0 + \phi_1 * X_m + \omega_m \tag{9}$$

Because the dependent variable in this second-stage regression is generated from the earlier "first-stage" analysis, we do not estimate Equation (9) by OLS. Instead we make two adjustments. First, we weight each observation by the inverse of the estimated variance of the β_m term, which we calculate using the bootstrap trial estimates of the β_m's from the first stage.[43] Second, in order to conduct inference, we empirically approximate the distribution of the second-stage coefficients (ϕ's) by repeatedly estimating Equation (9) using the sets of β_m from the bootstrap trials of Equation (7). The reported standard errors are the standard deviation of the ϕ coefficient from this bootstrapped distribution.

[43] One key source of heteroskedasticity is that the major-gender cells are differently sized, on average. Estimates of percentage changes in share for smaller majors are substantially more variable, and this weighting ensures that small majors do not exert undue influence on these estimates. In practice, the choice to weight has relatively little impact on the coefficients, although the coefficient estimates are more stable across specifications that include different numbers of major categories (for example, due to data not being available from B&B).

Table A-9: Descriptive Statistics for Correlates of Major Cyclicality

	No. Obs.	Mean	Std. Dev.
Panel A: Women			
ACS Variables			
Change in Log(Share) with 1 ppt unemp - Women	38	0.009	0.044
Share with Graduate Degree (Age 35-45)	38	0.387	0.134
Long-run average Female Share of Major	38	0.592	0.187
Share living in state of birth (Age 35-45)	38	0.526	0.070
HHI of occupations (Age 35-45)	38	0.086	0.122
Median Log(Wage) Ages 35-45 - Women	38	3.248	0.178
Share Working FTFY (35-45) - Women	38	0.600	0.053
B&B Variables			
Average GPA for Major Courses	33	3.344	0.083
Average Math GPA	28	2.617	0.233
Number of Job Interviews w/in first year	32	5.243	1.555
Median SAT Math Score	31	5.337	0.445
Median Number of Math Credits	34	4.178	4.723
Share Employed at 1 year	34	0.853	0.055
Share in Unrelated Jobs in first year	34	0.490	0.159
Panel B: Men			
ACS Variables			
Change in Log(Share) with 1 ppt unemp - Men	38	0.004	0.035
Share with Graduate Degree (Age 35-45)	38	0.350	0.145
Long-run average Female Share of Major	38	0.482	0.173
Share living in state of birth (Age 35-45)	38	0.510	0.067
HHI of occupations (Age 35-45)	38	0.049	0.080
Median Log(Wage) Ages 35-45 - Men	38	3.457	0.172
Share Working FTFY (35-45) - Men	38	0.840	0.041
B&B Variables			
Average GPA for Major Courses	33	3.311	0.090
Average Math GPA	28	2.616	0.239
Number of Job Interviews w/in first year	32	6.046	1.478
Median SAT Math Score	31	5.437	0.439
Median Number of Math Credits	34	5.678	5.999
Share Employed at 1 year	34	0.865	0.053
Share in Unrelated Jobs in first year	34	0.476	0.147

Source: Authors' calculations from ACS and B&B data. Majors are weighted using the same weights as in Tables 1-2, which are gender specific. These weights are not equal to the long-run shares of the major categories, which is why the weighted averages of the changes in log(share) are not equal to zero. The variables listed with "- Women" or "- Men" are calculated based on underlying data limited to the respective gender. The other variables are calculated using all available observations in the source datasets. Thus, any differences between panels for these variables reflect differences in weights.

Table A-10: Correlates of Cyclical Changes in Major Shares

Characteristic of Major	Women			Men		
Labor Market Prospects - Long Run						
Median Log(Wage) Ages 35-45	0.135	***	(0.019)	0.114	***	(0.019)
Share Working FTFY (35-45)	0.478	***	(0.066)	0.551	***	(0.073)
Labor Market Prospects - Short Run						
Number of Job Interviews w/in first year	0.011	***	(0.003)	0.007	**	(0.003)
Share Employed at 1 year	0.240	***	(0.047)	0.045		(0.046)
Share in Unrelated Jobs in first year	-0.163	***	(0.022)	-0.134	***	(0.015)
Difficulty						
Median SAT Math Score/100	0.027	***	(0.005)	0.026	***	(0.004)
Average Math GPA	0.050	***	(0.007)	0.045	***	(0.008)
Average GPA for Major Courses	-0.292	***	(0.039)	-0.132	***	(0.028)
Other						
Long-run average Female Share of Major	-0.085	***	(0.017)	-0.079	***	(0.022)
Share living in state of birth (Age 35-45)	-0.023		(0.026)	-0.016		(0.023)
HHI of occupations (Age 35-45)	-0.014		(0.009)	0.017		(0.026)
Share with a grad degree (Age 35-45)	-0.140	***	(0.020)	-0.030	*	(0.016)

Authors' calculations from ACS and B&B data. The dependent variable in each regression is the major-specific coefficient on the unemployment rate from Equation 7 using Log(Share) as the dependent variable. These coefficient estimates are available in Figures 3 and 4. Earnings and FTFY are calculated separately by gender. All other variables are calculated based on all graduates in the major category. See Appendix Table A-1 for a list of majors. Regressions using major characteristics calculated from the ACS include all 38 majors. Regressions using B&B characteristics have generally fewer observations due to data availability. Appendix Table A-9 provides summary statistics, including means, standard deviations and the number of valid observations for each of these characteristics. Observations are weighted by the inverse of the estimated variance of the dependent variable, which is calculated using the bootstrapping procedure described in the text. Bootstrapped standard errors in parentheses - see text for bootstrapping details. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

A-8 Results Robust to Cohort Composition

As discussed in section 4.3.1 of the main paper, we examined whether changes in the observable characteristics of cohorts drives changes in the major distribution of college completers. Table A-11 presents the results of this additional analysis. Each column represents the results from a separate multinomial logit regression of college major choice on the unemployment rate, major specific quadratic trends, and additional controls. Models are run separately for women (Panel A) and for men (Panel B). For each specification, we capture the major-specific marginal effects (semi-elasticities) resulting from a one percentage point increase in the unemployment rate. We then correlate these marginal effects with the same results from the baseline specification. This correlation is therefore 1 by construction for column (1). We also conduct the second-stage analysis that regresses these coefficients on median log earnings. The results reveal that controlling for race, region, or both together leads to negligible changes in the key results.

Table A-11: Multinomial Logit Regression with Controls for Race and Region

	(1)	(2)	(3)	(4)
Panel A: Women				
Correlation with Baseline Coefficients	1	0.9998	1	0.9998
Coefficient on Median Log Wage	0.1287	0.1268	0.1297	0.1279
R-squared	0.3054	0.2937	0.3089	0.2977
Panel B: Men				
Correlation with Baseline Coefficients	1	0.9997	0.9998	0.9994
Coefficient on Median Log Wage	0.1119	0.1102	0.1143	0.1127
R-squared	0.3115	0.2990	0.3210	0.3086
Control for Region	N	Y	N	Y
Control for Race	N	N	Y	Y

Authors' calculations from ACS and B&B data. The table presents sensitivity analysis to the inclusion of controls for race and region. Separately for men and women, the table provides the correlation with the baseline distribution of cyclicality, the second-stage coefficient on median log wage, and the R-squared from the second-stage regression. Column (1) replicates the estimates in the baseline specification using multinomial logit estimation. Columns (2), (3), and (4) add full interactions of region, race, and region by race, respectively. The data used in these MNL regressions is collapsed at the gender, graduation year, major, region, race level.

As also discussed in section 4.3.1, we provide results allowing for a quadratic relationship between the percent of a cohort enrolled/completed and the share of the cohort choosing a major. Tables A-12 and A-13 provide these results for men and women, respectively. In these tables, the baseline refers to the coefficient estimates underlying the results reported in Table 5, column (2). In each table, the first column shows the baseline estimates, while the second column shows the major cyclicality estimates from a specification that allows for each major's share to depend on the cohort's enrollment share linearly. The third column shows similar results while allowing each major's share to depend on the enrolled share of the cohort using a quadratic functional form. The fourth and fifth columns are analogous to the second and third columns using the share of the cohort completing the degree rather than the share enrolling as the key control. The results are not very sensitive to the choice of functional form of the enrollment or completion controls, with columns (2) and (3) quite similar and columns (4) and (5) also quite similar. For men, the correlations between columns (2) and (3) and (4) and (5), respectively, are each over 0.99, while for women, the correlation between columns (2) and (3) is over 0.99 and between columns (4) and (5) is 0.94.

Table A-12: Log Share Regressions Controlling Flexibly for Enrollment and Completion - Men

Major	(1) Baseline		(2) Linear Enrollment		(3) Quadratic Enrollment		(4) Linear Completion		(5) Quadratic Completion	
Accounting	0.0398	***	0.0343	***	0.0339	***	0.0309	***	0.0307	***
Actuarial Science	0.0694		0.0788		0.0818		0.0634		0.0638	
Agriculture	0.0212	**	0.0112		0.0113		-0.0054		-0.0055	
Architecture	-0.0133		-0.0055		-0.0056		-0.0128		-0.0124	
Biology Fields	0.0093		0.0347	***	0.0342	***	0.0261	*	0.0263	*
Business Fields, not Finance	-0.0120	*	-0.0264	***	-0.0264	***	-0.0294	***	-0.0297	***
Chemistry and Pre-Med	0.0442	***	0.0330	***	0.0329	***	0.0276	***	0.0278	***
Communications Fields	0.0017		0.0092		0.0090		-0.0052		-0.0052	
Computer-Related Fields	0.0172		0.0192		0.0187		-0.0033		-0.0044	
Early and Elementary Education	-0.0739	***	-0.0513	***	-0.0511	***	-0.0388	*	-0.0377	**
Economics	0.0005		-0.0158		-0.0161		-0.0071		-0.0072	
Education Fields, Other	-0.0377	***	-0.0222	**	-0.0217	**	-0.0115		-0.0111	
Engineering Fields	0.0422	***	0.0131	**	0.0135	**	0.0080		0.0076	
Environmental and Natural Resource Fields	0.0203		0.0548	**	0.0542	**	0.0352		0.0357	
Family and Consumer Sciences	-0.0257		-0.0019		-0.0021		-0.0031		-0.0031	
Finance	0.0094		-0.0108		-0.0110		-0.0153		-0.0156	
Industrial and Commercial Arts	-0.0135		-0.0235	**	-0.0237	**	-0.0261	**	-0.0259	**
Journalism	-0.0088		-0.0019		-0.0021		-0.0155		-0.0155	
Leisure Studies	-0.0057		0.0536	***	0.0520	***	0.0463	*	0.0465	*
Liberal Arts and History Fields	-0.0300	***	-0.0183	***	-0.0183	***	-0.0098	*	-0.0093	**
Literature and Languages Fields	-0.0408	***	-0.0198	**	-0.0200	**	0.0012		0.0019	
Mathematics and Statistics	0.0087		0.0091		0.0096		0.0256	*	0.0255	*
Natural Science Fields, Other	0.0519	***	0.0538	***	0.0545	***	0.0416	***	0.0416	***
Nursing	0.0272		0.0614	***	0.0612	***	0.0412	**	0.0415	**
Other Fields	-0.0041		-0.0092		-0.0091		-0.0184		-0.0188	
Pharmacy	0.0397	**	0.0402	*	0.0404	*	0.0360		0.0364	
Physics	0.0280	**	0.0108		0.0114		0.0181		0.0182	
Political Science and International Relations	-0.0240	**	0.0019		0.0013		0.0128		0.0130	
Pre-Law and Legal Studies	0.0084		-0.0012		-0.0013		-0.0059		-0.0059	
Protective Services	0.0210		0.0415	***	0.0404	***	0.0353	**	0.0356	**
Psychology Fields	-0.0304	**	0.0089		0.0083		0.0179		0.0183	
Public Affairs, Health, Policy	0.0390	***	0.0448	***	0.0449	***	0.0362	**	0.0362	**
Social Science Fields, Other	-0.0318	***	0.0016		0.0013		0.0086		0.0090	
Social Work	0.0059		0.0428	*	0.0428	*	0.0362		0.0361	
Sociology	-0.0816	***	-0.0276	**	-0.0274	**	-0.0079		-0.0073	
Technical Engineering Fields	0.0048		-0.0016		-0.0017		-0.0022		-0.0027	
Technical Health Fields	0.0139		0.0466	***	0.0464	***	0.0384	***	0.0385	***
Visual and Performing Arts	-0.0106		0.0084		0.0083		-0.0019		-0.0018	

Note: Column (1) represents the baseline national coefficients using the 1960–2013 sample and nonparametric estimation with a bandwidth of seven years. Column (2) includes major-specific interactions with the cohort enrollment rate. Column (3) includes major-specific interactions with both a linear and quadratic cohort enrollment rate. Column (4) includes major-specific interactions with the cohort completion rate, while Column (5) includes major-specific interactions with both a linear and quadratic cohort rate. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A-13: Log Share Regressions Controlling Flexibly for Enrollment and Completion - Women

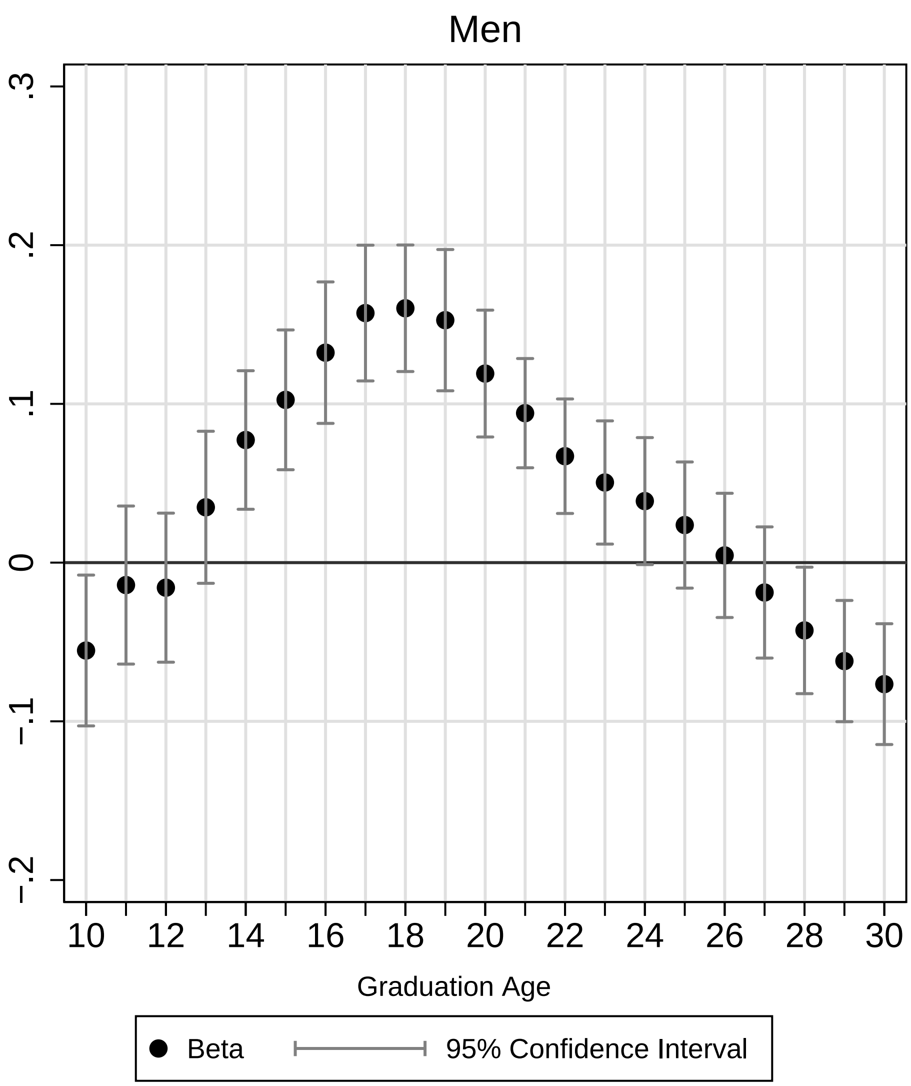
Major	(1) Baseline		(2) Linear Enrollment		(3) Quadratic Enrollment		(4) Linear Completion		(5) Quadratic Completion	
Accounting	0.0359	**	0.0435	***	0.0385	**	0.0390	**	0.0271	
Actuarial Science	0.0373		0.0594		0.0180		0.0900	*	0.0308	
Agriculture	0.0873	***	0.1126	***	0.1110	***	0.1080	***	0.0979	**
Architecture	-0.0067		0.0182		0.0118		0.0204		0.0023	
Biology Fields	0.0259	**	0.0335	***	0.0362	***	0.0351	***	0.0376	***
Business Fields, not Finance	0.0135		0.0165		0.0112		0.0096		-0.0015	
Chemistry and Pre-Med	0.0423	***	0.0302	***	0.0310	***	0.0193	*	0.0228	**
Communications Fields	0.0233	**	0.0313	**	0.0280	**	0.0295	**	0.0197	
Computer-Related Fields	0.0448		0.0662	*	0.0538	*	0.0623	*	0.0353	
Early and Elementary Education	-0.0508	***	-0.0553	***	-0.0505	***	-0.0490	***	-0.0363	***
Economics	0.0287	**	0.0213		0.0126		0.0079		-0.0076	
Education Fields, Other	-0.0303	***	-0.0302	***	-0.0269	***	-0.0242	***	-0.0161	*
Engineering Fields	0.0978	***	0.1021	***	0.0951	***	0.0859	***	0.0680	**
Environmental and Natural Resource Fields	0.0616		0.1156	***	0.1158	***	0.1299	***	0.1170	***
Family and Consumer Sciences	-0.0049		-0.0028		0.0009		-0.0013		0.0060	
Finance	0.0211		0.0202		0.0157		0.0080		-0.0014	
Industrial and Commercial Arts	0.0136		0.0193	*	0.0164		0.0165		0.0091	
Journalism	0.0106		0.0232	**	0.0178		0.0224	*	0.0077	
Leisure Studies	0.0396	**	0.0676	***	0.0665	***	0.0739	***	0.0636	***
Liberal Arts and History Fields	-0.0254	***	-0.0298	***	-0.0277	***	-0.0282	***	-0.0218	***
Literature and Languages Fields	-0.0390	***	-0.0427	***	-0.0412	***	-0.0364	***	-0.0313	**
Mathematics and Statistics	-0.0021		-0.0046		-0.0093		-0.0028		-0.0133	
Natural Science Fields, Other	0.0341	***	0.0365	***	0.0371	***	0.0328	***	0.0323	***
Nursing	0.0370	***	0.0361	***	0.0373	***	0.0311	***	0.0320	***
Other Fields	0.0256	*	0.0580	***	0.0535	***	0.0687	***	0.0533	***
Pharmacy	0.0537	***	0.0627	***	0.0644	***	0.0631	***	0.0597	***
Physics	0.0041		0.0009		0.0012		-0.0031		-0.0045	
Political Science and International Relations	0.0044		0.0050		0.0031		0.0047		0.0007	
Pre-Law and Legal Studies	0.0094		0.0195		0.0184		0.0202		0.0143	
Protective Services	0.0400	**	0.0589	***	0.0633	***	0.0626	***	0.0648	***
Psychology Fields	-0.0111		0.0036		0.0063		0.0154	***	0.0165	***
Public Affairs, Health, Policy	0.0341	***	0.0466	***	0.0436	***	0.0467	***	0.0356	**
Social Science Fields, Other	-0.0311	**	-0.0132		-0.0118		0.0001		-0.0008	
Social Work	-0.0090		0.0064		0.0065		0.0128		0.0092	
Sociology	-0.0647	***	-0.0479	***	-0.0450	***	-0.0301	**	-0.0265	*
Technical Engineering Fields	0.0191		0.0344		0.0279		0.0280		0.0084	
Technical Health Fields	0.0366	***	0.0451	***	0.0466	***	0.0461	***	0.0452	***
Visual and Performing Arts	-0.0051		0.0014		0.0033		0.0046		0.0066	

Note: Column (1) represents the baseline national coefficients using the 1960–2013 sample and nonparametric estimation with a bandwidth of seven years. Column (2) includes major-specific interactions with the cohort enrollment rate. Column (3) includes major-specific interactions with both a linear and quadratic cohort enrollment rate. Column (4) includes major-specific interactions with the cohort completion rate, while Column (5) includes major-specific interactions with both a linear and quadratic cohort rate. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

A-9 Autocorrelation of National Unemployment Rates

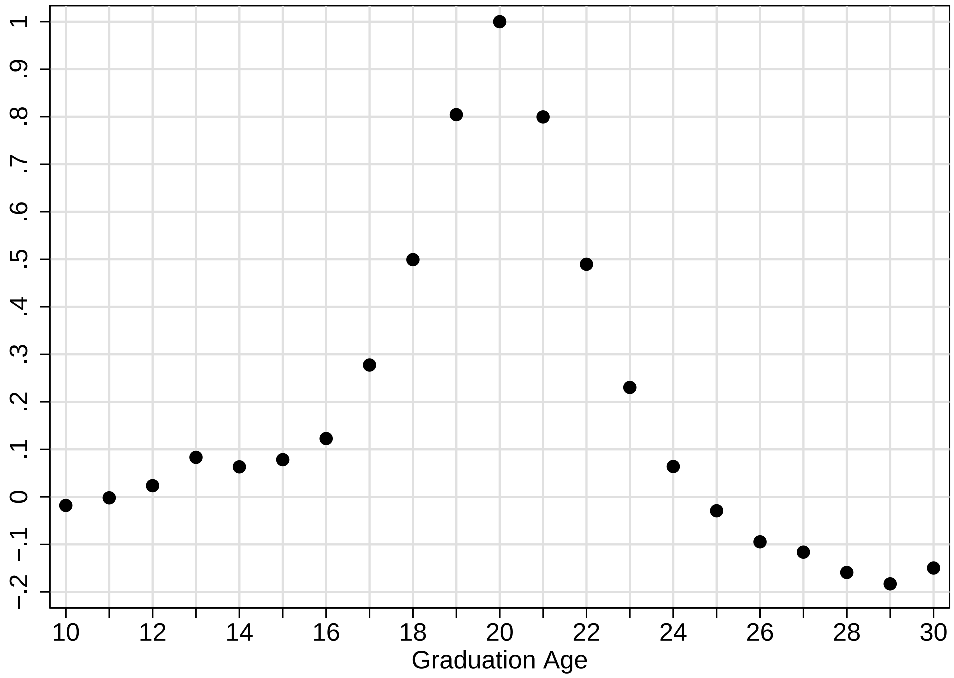
Figure 8 in the main text showed that the results for women are robust to the age at which we measure the unemployment rate. For completeness, Appendix Figure A-7 shows that the results for men are similarly robust. Additionally, Appendix Figure A-8 presents autocorrelation coefficients in unemployment rates for the sample used in that figure. As expected, the unemployment rate a cohort faces at age 20 is strongly positively correlated with the unemployment rate that same cohort faces at ages 19 and 21, and it is moderately correlated with unemployment rates at ages 18 and 22. Correlations are substantially weaker for ages more than two years away from age 20.

Figure A-7: Relationship between Long-Run Earnings and Major Cyclicality, by Reference Age of Unemployment



Data sources: BLS and authors' calculations from 2009–2018 ACS data. The figure plots coefficient estimates from separate regressions of the second stage relationship between long-run earnings and major cyclicality, varying the age at which the unemployment rate is measured when calculating major cyclicality. The confidence intervals are plotted using the bootstrap standard errors. In calculating bootstrap SEs, the sample only includes the cohorts born in 1960–1989 (as opposed to the original sample of the 1960–1993 birth cohorts) such that every cohort in the sample has corresponding unemployment rates for the full range of ages.

Figure A-8: Autocorrelation of National Unemployment Rates



Source: BLS and ACS data. The figure shows the autocorrelation in unemployment rates by age for the sample used in Figure 8.

A-10 Analysis using State-Level Unemployment Rates

As discussed in the main text, our preferred specifications use national unemployment rates rather than local unemployment rates to provide identifying variation in the state of the business cycle. We prefer these specifications both because college-educated workers are part of a national labor market and because the the ACS contains only state of birth, which is a coarse measure of the local labor market an individual is likely to consider upon graduation. Nevertheless, for completeness, Tables A-14 and A-15 provide the results from alternative specifications that use state-level unemployment rates instead.

The first column replicates the baseline results using national major-cohort cells for the full 1960–2013 period. The second column restricts the sample to 1976–2013, the period when state unemployment rates are widely available, which serves as the baseline for the remaining columns in the table. Column (3) uses state of birth-major-cohort cells but continues to use the national unemployment rate as the measure of the state of the business cycle. These results are quite similar to the national cell approach; the coefficients are strongly correlated (+.96 for women, +.87 for men) and the second-stage coefficient on median log earnings is quite similar. The fourth column maintains the sample in column (2) but replaces the national unemployment rate with the state unemployment rate. Again the results are qualitatively similar, although the second-stage coefficient is only half as large as in the baseline specification.

Table A-14: Log Share Regressions Using National and State Unemployment Rates for Women

	(1)		(2)		(3)		(4)	
Correlation with 1976-2013 Baseline Beta	0.5830		1		0.9557		0.9515	
Coefficients on Median Log Wage	0.1352		0.0842		0.0757		0.0440	
R-squared	0.2955		0.3867		0.2433		0.2194	
Accounting	0.0775	***	0.0444	***	0.0467	***	0.0211	***
Actuarial Science	0.0235		0.0319		0.0280		0.0320	
Agriculture	0.1168	***	-0.0282	*	-0.0311	**	-0.0094	
Architecture	0.0208		-0.0381	***	-0.0469	***	-0.0301	**
Biology Fields	0.0084		-0.0162	**	-0.0252	**	-0.0197	***
Business Fields, not Finance	0.0470	***	0.0162		0.0174		0.0120	*
Chemistry and Pre-Med	0.0309	***	-0.0081		-0.0164	**	-0.0127	
Communications Fields	0.0377	***	0.0205	*	0.0158		0.0195	**
Computer-Related Fields	0.1103	***	0.0759	**	0.0875	***	0.0451	**
Early and Elementary Education	-0.0670	***	-0.0318	***	-0.0216	***	-0.0157	***
Economics	0.0654	***	0.0244		0.0264	**	0.0182	*
Education Fields, Other	-0.0363	***	-0.0179	**	-0.0116	**	-0.0083	**
Engineering Fields	0.1393	***	0.0556	***	0.0635	***	0.0400	***
Environmental and Natural Resource Fields	0.0791	***	-0.0238		-0.0166		-0.0093	
Family and Consumer Sciences	-0.0144	*	-0.0415	***	-0.0282	***	-0.0213	***
Finance	0.0547	***	0.0148		0.0298	*	0.0208	*
Industrial and Commerical Arts	0.0238	***	-0.0114		-0.0123		-0.0096	
Journalism	0.0403	***	0.0020		0.0079		0.0011	
Leisure Studies	0.0339	**	-0.0359	***	-0.0418	***	-0.0249	**
Liberal Arts and History Fields	-0.0367	***	-0.0203	***	-0.0243	***	-0.0173	***
Literature and Languages Fields	-0.0602	***	-0.0039		-0.0221	**	-0.0166	**
Mathematics and Statistics	0.0060		0.0490	***	0.0700	***	0.0379	***
Natural Science Fields, Other	0.0373	***	0.0089		-0.0040		-0.0035	
Nursing	0.0483	***	0.0076		0.0001		-0.0015	
Other Fields	0.0279	**	-0.0009		0.0149		-0.0007	
Pharmacy	0.0860	***	0.0557	***	0.0614	***	0.0379	***
Physics	-0.0029		0.0075		0.0314		0.0115	
Political Science and International Relations	0.0053		0.0109		-0.0027		-0.0048	
Pre-Law and Legal Studies	0.0302	***	0.0267		0.0486	***	0.0295	***
Protective Services	0.0487	***	-0.0078		-0.0231	**	-0.0061	
Psychology Fields	-0.0235	***	-0.0038		-0.0071		-0.0008	
Public Affairs, Health, Policy	0.0413	***	0.0038		0.0164		0.0111	
Social Science Fields, Other	-0.0469	***	-0.0304	**	-0.0317	***	-0.0234	**
Social Work	-0.0013		-0.0234	**	-0.0259	**	-0.0164	*
Sociology	-0.0863	***	-0.0428	***	-0.0514	**	-0.0311	***
Technical Engineering Fields	0.0794	***	0.0081		0.0243	*	0.0045	
Technical Health Fields	0.0405	***	0.0041		0.0056		0.0014	
Visual and Performing Arts	-0.0095		-0.0341	***	-0.0346	***	-0.0215	***

Note: Column (1) represents the baseline national coefficients using the 1960–2013 sample. Column (2) represents the baseline national coefficients using the 1976–2013 sample. Column (3) shows coefficients from using state-level cells, national unemployment rates, and national trends. Column (4) shows the state-level coefficients with state unemployment rates, and national quadratic trends. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A-15: Log Share Regressions Using National and State Unemployment Rates for Men

	(1)		(2)		(3)		(4)	
Correlation with 1976-2013 Baseline Beta	0.8427		1		0.8695		0.8828	
Coefficients on Median Log Wage	0.1145		0.0786		0.0550		0.0447	
R-squared	0.3064		0.3996		0.2046		0.2542	
Accounting	0.0617	***	0.0328	***	0.0325	***	0.0216	**
Actuarial Science	0.0393		0.0474		0.0534		0.0217	
Agriculture	0.0240	**	-0.0080		0.0022		-0.0009	
Architecture	-0.0006		-0.0188	*	-0.0075		-0.0146	
Biology Fields	0.0020		-0.0078		-0.0100		-0.0110	
Business Fields, not Finance	0.0004		-0.0140	**	-0.0159	**	-0.0083	**
Chemistry and Pre-Med	0.0372	***	0.0146	*	0.0125		0.0031	
Communications Fields	0.0111	**	-0.0046		-0.0025		-0.0064	
Computer-Related Fields	0.0481	***	0.0243		0.0280		0.0198	
Early and Elementary Education	-0.1096	***	-0.0597	***	-0.0273		-0.0279	
Economics	0.0083		0.0052		-0.0005		0.0028	
Education Fields, Other	-0.0513	***	-0.0188	*	-0.0107		-0.0073	
Engineering Fields	0.0525	***	0.0290	***	0.0238	***	0.0146	***
Environmental and Natural Resource Fields	0.0111		-0.0118		-0.0054		-0.0056	
Family and Consumer Sciences	-0.0420	***	-0.0258		0.0294		0.0026	
Finance	0.0208	*	0.0076		0.0069		0.0047	
Industrial and Commerical Arts	-0.0363	***	-0.0259	**	-0.0243	**	-0.0214	**
Journalism	0.0160		-0.0184		-0.0120		0	
Leisure Studies	-0.0380	**	-0.0279		-0.0138		-0.0289	**
Liberal Arts and History Fields	-0.0424	***	-0.0182	**	-0.0157	**	-0.0149	**
Literature and Languages Fields	-0.0644	***	-0.0078		-0.0117		-0.0150	
Mathematics and Statistics	0.0034		0.0333	***	0.0281	***	0.0215	***
Natural Science Fields, Other	0.0577	***	0.0382	***	0.0390	***	0.0168	
Nursing	0.0438	***	0.0168		0.0342	**	0.0308	**
Other Fields	0.0033		-0.0086		-0.0107		-0.0002	
Pharmacy	0.0557	***	0.0364		0.0353	**	0.0182	
Physics	0.0197	**	0.0228	**	0.0212	*	0.0087	
Political Science and International Relations	-0.0192	**	0.0016		-0.0207		-0.0104	
Pre-Law and Legal Studies	-0.0025		0.0105		0.0268		0.0164	
Protective Services	0.0195	*	0.0161		0.0086		0.0082	
Psychology Fields	-0.0386	***	-0.0092		-0.0133		-0.0030	
Public Affairs, Health, Policy	0.0431	***	0.0245		0.0320		0.0187	
Social Science Fields, Other	-0.0490	***	-0.0229	*	-0.0062		-0.0052	
Social Work	0.0218		0.0292		0.0348	*	0.0311	**
Sociology	-0.1097	***	-0.0409	*	-0.0300	*	-0.0273	*
Technical Engineering Fields	0.0340	***	0.0241	**	0.0398	**	0.0297	***
Technical Health Fields	0.0189	*	0.0215	*	0.0332	***	0.0192	**
Visual and Performing Arts	-0.0187	**	-0.0312	***	-0.0286	***	-0.0344	***

Note: Column (1) represents the baseline national coefficients using the 1960–2013 sample. Column (2) represents the baseline national coefficients using the 1976–2013 sample. Column (3) shows coefficients from using state-level cells, national unemployment rates, and national trends. Column (4) shows the state-level coefficients with state unemployment rates, and national quadratic trends. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

A-11 No evidence that marginal individuals end up in tails of wage distribution

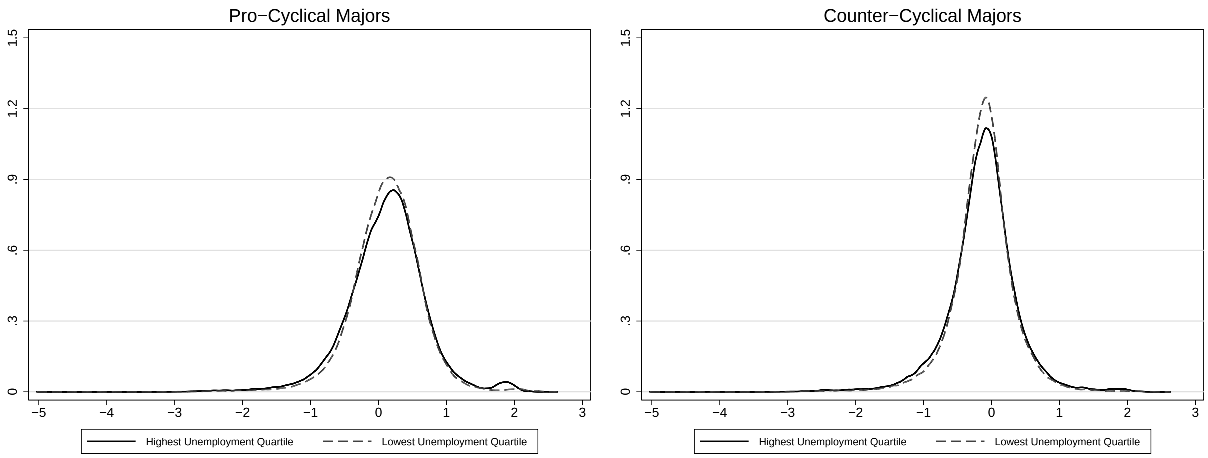
As discussed in the main text, we considered the possibility that individuals choosing a different major as a result of the business cycle may have less of a comparative advantage in their eventual major than in their counterfactual major. For example, the marginal business or engineering student may be poorly prepared and end up with a smaller earnings gain than the average difference in earnings between individuals with these degrees and others. To address this hypothesis, we examine the earnings distributions for four categories of individuals based on whether their chosen major is procyclical and whether they graduated in a high or low unemployment environment. If students end up more poorly matched, we would expect higher density in the left tail of the distribution of the earnings of individuals in countercyclical majors who graduated in times of high unemployment.

We begin by calculating earnings residuals, controlling for age, highest degree (sample limited to those with at least a bachelor's degree), survey year, race, and state of residence. We then calculate the distribution of these residuals by the four categories discussed above. Pro-cyclical majors are those with statistically significant negative losses in share as the unemployment rise, while counter-cyclical majors are those that have statistically significant gains in share. The high unemployment cohorts are those who experienced an unemployment rate in the top quartile of observed rates at age 20; the low unemployment cohorts experienced an unemployment rate in the bottom quartile.

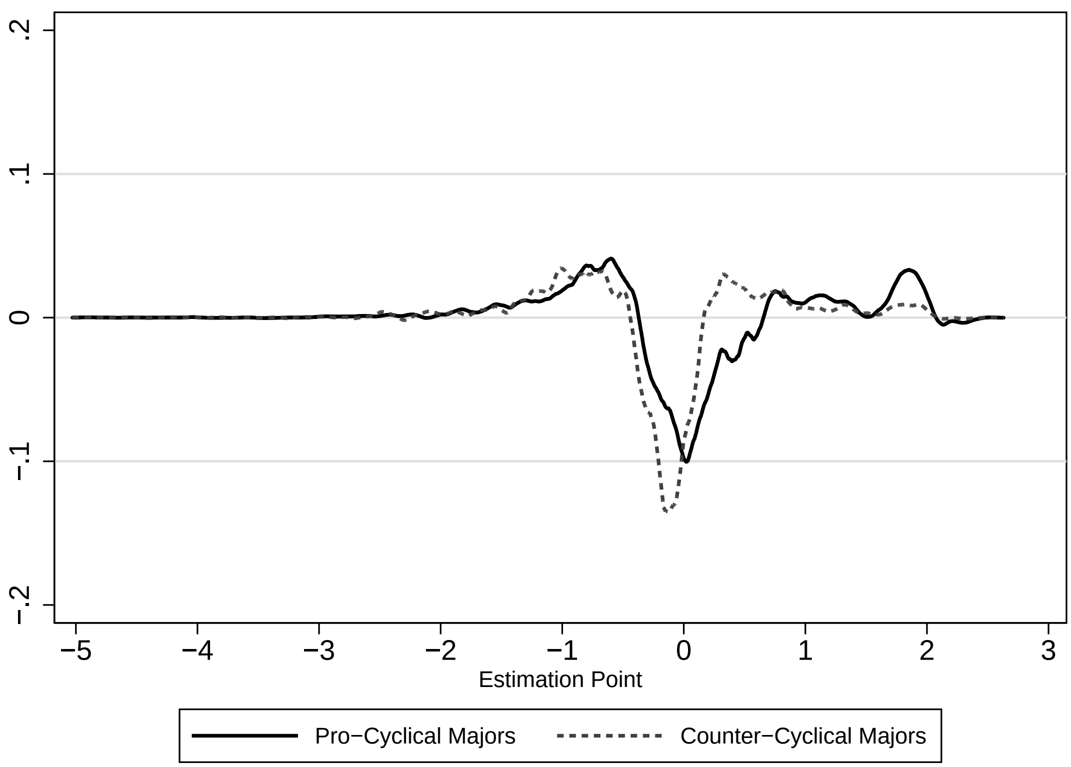
Figures A-9 and A-10 provide the results of this exercise for women and for men respectively. For both types of majors, there is a leftward shift in the middle of the distribution when comparing high unemployment rate cohorts to low unemployment rate cohorts. This shift is consistent with the literature finding long-run negative effects of entering the labor market in a recession. There is not, however, a noticeable increase in the density of low earning (left tail) individuals in the countercyclical majors. These results suggest that individuals who select a different major as a result of the business cycle have earnings that are distributed similarly to the inframarginal individuals who select the same major regardless of the state of the business cycle.

Figure A-9: Log Wage Residuals for Women

(a) Distribution of Wage Residuals by Unemployment Rate



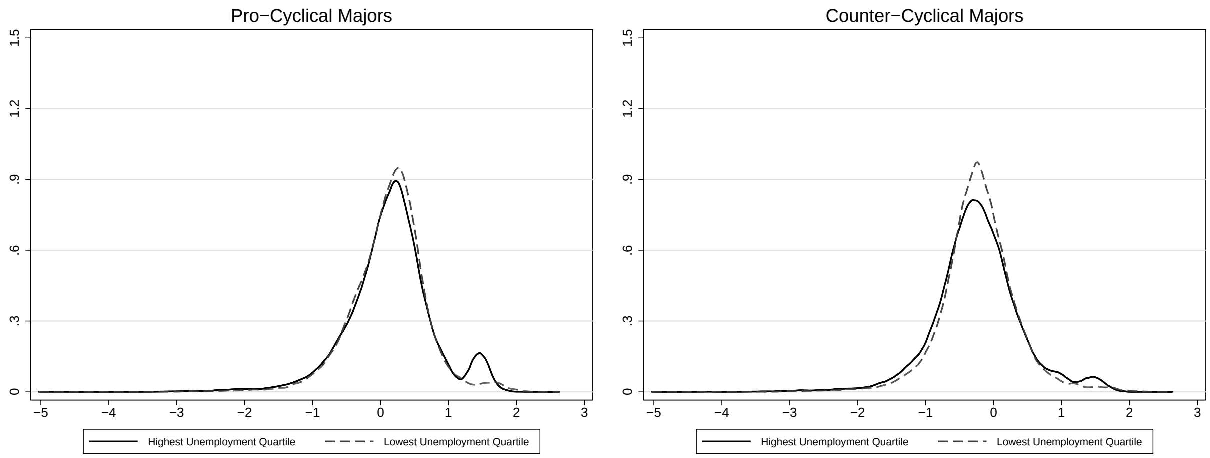
(b) Difference in Wage Residual Densities (Highest-Lowest Unemployment Rate Quartile)



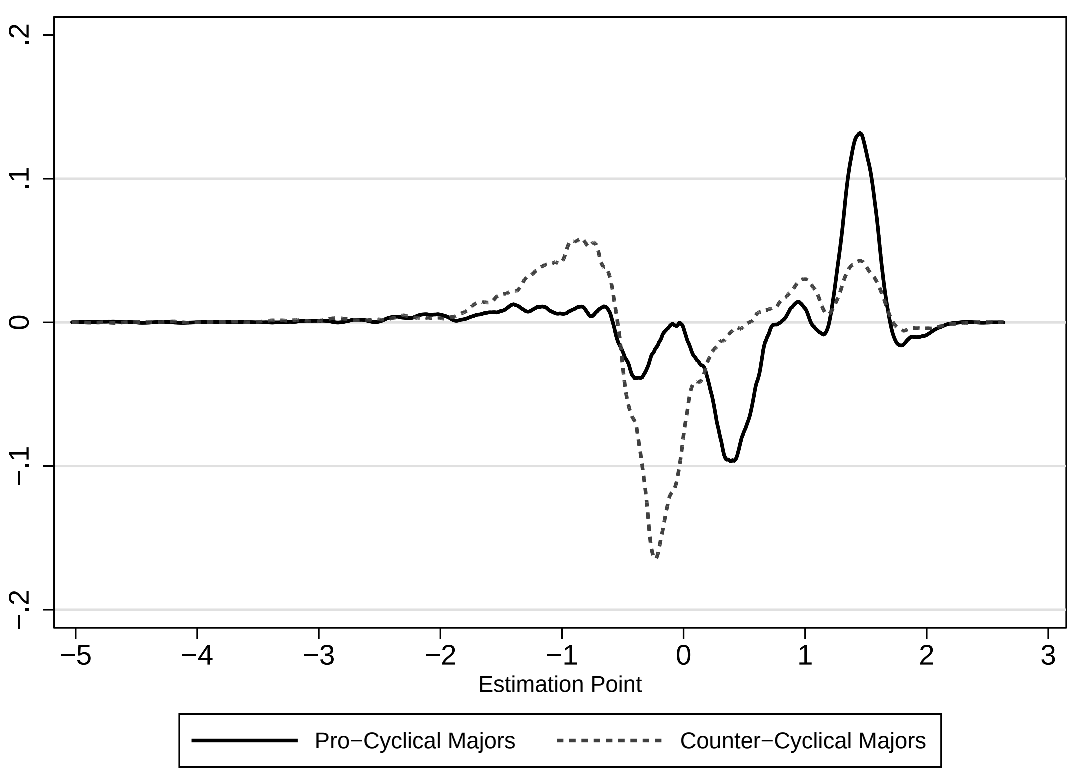
Note: The lines in the bottom panel represent the difference in estimated densities for each of the graphs in the top panel.

Figure A-10: Log Wage Residuals for Men

(a) Distribution of Wage Residuals by Unemployment Rate



(b) Difference in Wage Residual Densities (Highest-Lowest Unemployment Rate Quartile

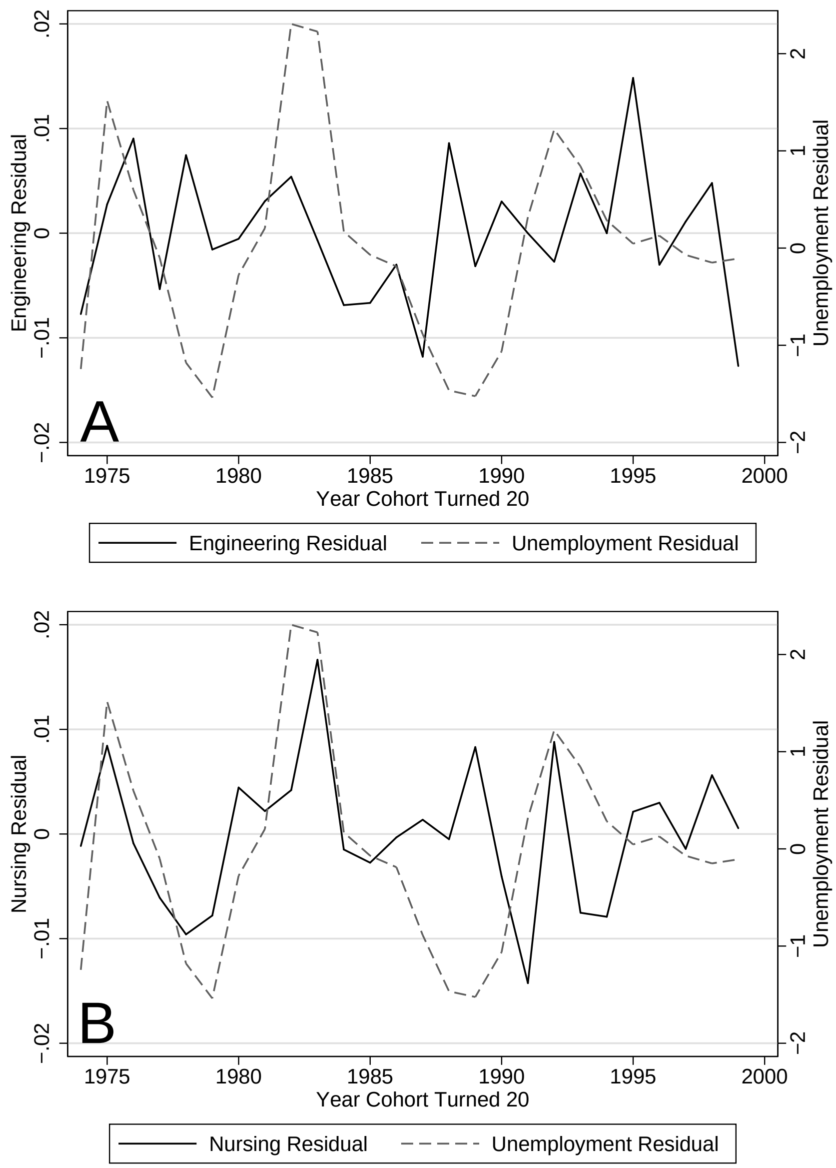


Note: The lines in the bottom panel represent the difference in estimated densities for each of the graphs in the top panel.

A-12 No evidence that marginal individuals less likely to work in chosen field

This pair of graphs shows the de-trended share of individuals working in the most closely related field over time for two well-defined majors - Engineering (working as engineers) in Panel A and Nursing (working as nurses) in Panel B. Among Engineering majors, there is no discernible relationship between the share working as engineers and the unemployment rate. For Nursing majors, there appears to be a positive relationship. Thus, if anything, marginal students induced to study Nursing based on a high unemployment rate are *more likely* to end up working as nurses, which suggests that they reap the rewards of the higher earning capacity associated with the nursing degree.

Figure A-11: Cyclical Relationship Between Share Working in a Related Field and the Unemployment Rate



Note: Each of the time series plots represents the deviation of the series around a quadratic trend.

A-13 Implications for Graduating in a Recession

Section 4 of the main paper establishes that students respond to increases in the unemployment rate by selecting more difficult majors that command higher earnings levels in the labor market. However, to our knowledge, no empirical analysis of the earnings losses of graduating in a recession incorporates the impact of this compensating behavior. In this portion of the appendix, we use our earlier results to quantify how much larger the costs of graduating in a recession would be in the absence of this labor "supply" adjustment. To fix ideas, consider the following analytical framework:

Suppose that the earnings of a cohort shortly following a recession, $log(earnings)_c$, are a function of demand conditions at graduation ($unempgrad$) and the average market value of the cohort's selected majors ($majorval$):

$$log(earnings)_c = \beta_0 + \beta_1 unempgrad_c + \beta_2 majorval_c + \epsilon_c \tag{10}$$

Assume that when both the unemployment rate and the value of the major are included in a regression model that the coefficient on $unempgrad_c$ is the effect of the unemployment rate on $log(earnings)$ due to demand conditions alone, i.e. after accounting for any supply-side changes in human capital.[44] Previous analysis, instead, estimates the relationship between the earnings of a cohort and the unemployment rate in the context of a "short" regression without the control:

$$log(earnings)_c = \tilde{\beta_0} + \tilde{\beta_1} unempgrad_c + \tilde{\epsilon_c} \tag{11}$$

with the well-known formula for the difference between these two coefficients:

$$\tilde{\beta_1} = \beta_1 + \beta_2 \frac{Cov(majorval, unempgrad)}{Var(unempgrad)} \tag{12}$$

Now suppose further that the unemployment rate at graduation does not directly affect the distribution of chosen majors (because it is too late to make adjustments), but that it is correlated with the unemployment rate midway through one's academic career, which does influence the set of majors selected by a cohort:

$$majorval_c = \gamma_0 + \gamma_1 unempmid_c + \eta_c \tag{13}$$

Again, relying on the assumption that the unemployment rate at graduation is unrelated to the residual in the major value equation, the expression in (12) simplifies to:

$$\tilde{\beta_1} = \beta_1 + \beta_2 \gamma_1 \delta_1 \tag{14}$$

[44] For simplicity, we discuss this regression without controls. It is straightforward to generalize this specification to one that includes a number of additional controls and to treat these three variables and the residual as having been purged of the influence of those controls. In this case, this assumption would be conditional on these controls.

with $\delta_1 = \frac{Cov(unempmid, unempgrad)}{Var(unempgrad)}$.

Therefore, the coefficient on the unemployment rate at graduation will be different depending on whether one controls for the composition of majors as long as the product $\beta_2\gamma_1\delta_1$ is not zero. The numerical value of this difference depends on slope coefficients from three regressions: 1) The "long" regression coefficient of earnings on major value (β_2); 2) A regression of major value on the unemployment rate midway through school (γ_1); and 3) A regression of the unemployment rate midway through school on the unemployment rate at graduation (δ_1).

We now estimate or approximate these three objects. Doing so first requires a more exact definition of the average market value of the cohorts' selected majors, *majorval*. In the analysis that follows, we calculate *majorval* for each cohort as the weighted average of the median mid-career (ages 35-45) log(earnings) associated with the distribution of majors selected by that cohort. Importantly, we treat the earnings potential of majors as constant across cohorts, but the weights on each major, ω_{jc}, change from cohort to cohort.

In that case, we propose that a reasonable benchmark of β_2 is 1, which implies that the relative differences in earnings across majors in the years following graduation would be equal in percentage terms to those in mid-career. Imposing this value likely results in a conservative calculation, given that recessions tend to expand the earnings gaps between high-paying and low-paying majors (Oreopoulos, von Wachter, and Heisz 2012; Altonji, Kahn, and Speer 2016).

Next, to estimate γ_1, we consider two cohorts that experience different levels of unemployment during college. We can write the difference in the average of any permanent major characteristic ($\bar{x}$) across cohorts 0 and 1 as

$$\bar{x_1} - \bar{x_0} = \sum_j (\omega_{j1} - \omega_{j0}) x_j. \tag{15}$$

Evaluating this expression is straightforward given our estimates of how the shares of each major change with unemployment and a measure of mid-career earnings for each major. Specifically, suppose that cohort 0 faces average unemployment levels and cohort 1 faces unemployment that is 1 percentage point higher. Based on our earlier results, we can calculate the difference in share for each major as as $\omega_{j1} - \omega_{j0} = \left(e^{\beta_j^{unemp}} - 1\right) \cdot \omega_j^0$, and then multiply each difference in major share by that major's long-run earnings, $\bar{x}$.[45]

Taking the weighted sum of the changes in shares across all 38 majors yields approximately +0.5 log points. In other words, the increase in *permanent* earnings capacity of a cohort rises by roughly 0.5 percent with each percentage point increase in the unemployment rate it experiences at age 20 as a result of the change in the distribution of chosen majors.[46]

[45] Alternatively, we could use the results of the share level regressions, which would take the more straightforward form: $\omega_{j1} - \omega_{j0} = \beta_j^{unemp}$. In practice, this choice turns out to be immaterial because the results are so similar to each other.

[46] The weighted change in log(median earnings) with each one percentage point increase in the unemployment rate is 0.49 for men and 0.5 for women. In implementing these calculations, we adjust the changes in

The final coefficient, δ_1, is obtained from a regression of the unemployment rate at time t on the unemployment rate at time $t+2$, which over our time period yields a coefficient of $+0.43$.[47] This adjustment reflects the fact that economic conditions at the time of major choice are correlated with but not identical to those faced at the time of graduation.

Thus, a cohort graduating in a recession (with unemployment three percentage points higher than average) can be expected to have major-based earnings capacity that is $0.5 * 0.43 * 3 \approx 0.65$ log points higher than a cohort graduating with average unemployment.[48] The typical estimate of the negative effect of graduating in a recession is, in fact, an *underestimate* of the earnings losses due to weak demand at graduation because these effects are partially counterbalanced by a re-distribution of graduates toward more lucrative degrees.

In the absence of this compensating behavior, therefore, the effects of graduating in a recession would be more negative by approximately 0.65 log points. Compared to typical estimates in the -6 to -8 log point range (e.g. Kahn 2010), this offset is not insignificant. This is not to say that the previous literature on graduating in a recession is biased, rather our results can uniquely yield a decomposition of the combined effect of supply and demand, implying that the demand effect alone is roughly ten percent larger. Thus, even accounting for recession-induced changes to college majors, the average student who graduates during a recession likely experiences negative earnings as a result.

However, many students' chosen majors are presumably unaffected by the presence of a recession, which implies substantial heterogeneity in the effect of recessions on marginal and inframarginal individuals. Among those who choose different majors as a result of the recession, the recession likely induces a large increase in lifetime earnings, even when accounting for the negative labor demand effect at the time of graduation. For example, suppose that fifteen percent of the population switches majors in response to a recession, in line with our estimate for net switching among female students. In that case, those fifteen percent would see a nine percent increase in lifetime earnings capacity, while the other 85 percent are unchanged. Even if fully 30 percent of the population switches, our estimates imply that the average gains among switchers would be larger than the effect of the concurrent demand shock.

share to sum to zero across all majors, which is not required in the log(share) specification. We subtract from each major's change in share a portion of the total change in share that is proportional to the absolute value of the unadjusted change in share, requiring the resulting coefficients sum to zero.

[47]This specification is run using data from 1960–2013, and it includes the same quadratic trends used in the main analysis.

[48]This characterization of a "recession" is the same as used in Altonji, Kahn, and Speer (2016).