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

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Abstract

This paper examines the relationship between individuals' personal exposure to economic conditions and their investment choices in the context of human capital. Focusing on bachelor's degree recipients, we find that birth cohorts exposed to higher unemployment rates during typical schooling years select majors that earn higher wages, that have better employment prospects, and that more often lead to work in a related field. Much of this switching behavior can be considered a rational response to differences in particular majors' labor market prospects during a recession. However, higher unemployment leads to other meaningful changes in the distribution of majors. Conditional on changes in lifetime expected earnings, recessions encourage women to enter male-dominated fields, and students of both genders pursue more difficult majors, such as STEM fields. These findings imply that the economic environment changes how students select majors, possibly by encouraging them to consider a broader range of degree fields. Finally, in the absence of this compensating behavior, we estimate that the average estimated costs of graduating in a recession would be roughly ten percent larger.

JEL: E32, I23, J22, J24

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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 investment choices. Among firms, recessions are associated with reallocations of investment toward more productive uses (Davis and Haltiwanger 1990, Caballero and Hammour 1994). If exposure to recessions affects expectations and risk preferences, we should observe these changes borne out in individuals' allocative investment decisions as well. We focus on the decision to invest in human capital, one of the primary drivers of growth of the modern economy. There is substantial evidence that recessions affect the total amount of schooling received. 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 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 completers. Despite the fact that this decision is as crucial a driver of earnings potential as the enrollment decision itself, we know relatively little about how students choose college majors. 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 (Arcidiacono 2004, Zafar 2013).[2] This literature, however, has largely focused on a static "point-in-time" framework or based the analysis on a single cohort, largely due to data limitations.[3]

[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.

[2] A growing literature on major choice includes (but is not limited to) Arcidiacono, Hotz and Kang (2012), Beffy, Fougere and Maurel (2012), Betts (1996), Montmarquette, Cannings and Mahseredjian (2002), Stinebrickner and Stinebrickner (2014), Wiswall and Zafar (2015), and Zafar (2011).

[3] Recent work in Chile (Hastings, Neilson and Zimmerman 2013) and Norway (Kirkebøn, Leuven and

In this paper, we leverage new publicly available data on over 50 cohorts of 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? Previous studies have found a substantial influence of the business cycle on other facets of human capital investment including college enrollment (Betts and McFarland 1995, Hershbein 2012), college completion (Dynarski 2008, Kahn 2010), and graduate school attendance (Bedard and Herman 2008, Johnson 2013).[4] Additional research has investigated the role of economic conditions on the choice of specific careers, such as engineering (Freeman 1976) and investment banking (Oyer 2008). Yet to the best of our knowledge, this paper is the first to study the response to recession conditions by college students on the allocative margin of major choice.

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, short-run cyclical changes, 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, discussed in detail below, are gradual enough such that they can be well approximated by flexible major-specific trends. In order to draw causal inference, we assume 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.[5]

To answer this question empirically, we use data from the American Community Survey, which starting in 2009 collects data on field of study for all respondents with a Bachelor's degree. Unlike typical data sets with information on college major, such as the NLSY or Baccalaureate and Beyond, these new data from the ACS allow us to trace out the

Mogstad 2016) has exploited discontinuities in centralized admissions processes to provide new estimates of plausibly exogenous returns to different fields of study and degree programs.

[4]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. Charles, Hurst and Notowidigdo (2015) show that the impact of labor market conditions on educational attainment was especially pronounced during the housing boom and bust.

[5]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.

distribution of college majors among degree-holders for more than fifty birth cohorts who experienced substantial variation in labor market conditions immediately prior to entering the workforce. 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 five waves (2009-2013) of the ACS allow us to estimate major choices at a relatively fine level of aggregation. 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 and Katz 2009, Gemici and Wiswall 2014).

Figure 1 presents initial evidence that the distribution of college majors in a given cohort is starkly responsive to the business cycle. The dotted line in the figure shows the time-series from 1960 to 2011 of expected earnings for men with a Bachelor's degree who turned 20 during the reference year.[6] 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 solid 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.[7] 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 estimate how choices among 38 college major categories respond to the business cycle. Although data limitations preclude a direct analysis of the share of individuals whose choice of major changes in response to the business cycle, we find a substantial reallocation overall. For men, the fields with the largest gains in share are engineering, accounting, business, and the natural sciences. For women, the largest gains are in nursing, accounting, and computer-related fields. In contrast, students of both genders leave fields such as sociology and education-related fields during recessions. We further document that these patterns are robust to varying definitions

[6] 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.

[7] Because we do not observe the year of graduation for degree-holders, we use the unemployment rate that prevailed at age 20, which corresponds to the second year of college for someone who graduated high school at age 18 and enrolled immediately after. This imprecision likely induces measurement error in calculating the relevant unemployment rate at the time of major selection. We explore the importance of this choice of year in Section 3.4.1; the results show that the findings are robust to this choice.

of exposure to recessions, controlling for the changing composition of cohorts, and a variety of alternative specifications. Adding up the average marginal effects from a multinomial logit reveals that a one percentage point increase in the unemployment rate leads to a 3.2 percentage point total reallocation of majors for men, and a 4.1 percentage point reallocation for women. 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.

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? Using detailed data on major-specific characteristics from the ACS and Baccalaureate and Beyond 1993 data, we investigate a number of specific hypotheses. First, we examine the degree to which students are responding 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. We find that in response to recessions, students choose fields of study that are more challenging, require more math, and, above all, are higher paying. Both male and female students appear to be most strongly affected by median wages for prime-age workers in the occupations associated with the major, which explain 39 to 47 percent of the variation in major reallocation across the business cycle. These relationships are considerably stronger than are those with the number of job interviews or the share employed one year after completing college. For instance, majors with ten percent greater long-run median wages have a 1.8 percentage point more positive share elasticity in response to the unemployment rate for women and a 1.4 percentage point more positive share elasticity for men.

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 strong support for the view that students move into more difficult fields, and this relationship continues to hold, 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 imply that long-run earnings prospects alone are not a "sufficient statistic" for explaining the responsiveness of major choice to economic conditions.

Finally, using our answers to these two central questions, we can quantify how substantially this compensating behavior attenuates the costs of graduating in a recession. The economic consequences of graduating in a recession are well documented, as a growing literature has shown that students suffer from the timing of their exit from school (see, e.g. Oyer 2006, Kahn 2010, and Wee 2013). 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 (Kahn 2010, Hershbein 2012, Johnson 2013).

In contrast, 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. Thus, the typical average estimated costs of graduating in a recession likely understate the direct effect of graduating in a lower demand environment. In other words, the impact of graduating in a recession would be even more negative if students were unable to adjust on the margin of major choice. We estimate that the offsetting labor supply response along this intensive margin is roughly one-tenth of the demand effect of graduating in a recession, or 0.65 log points of expected earnings for "recession" conditions of an unemployment rate three percentage points above average.[8]

These results extend the prior research on human capital investment, which has primarily focused on the extensive margins of whether to enroll and complete additional years of post-secondary schooling.[9] This choice is a crucial one to make, as the wage gap between college and high school graduates is large (Grogger and Eide 1995, Carneiro, Heckman and Vytlacil 2011), and the completion of a college degree provides the option value for continuing on to advanced degrees (Stange 2012). Several studies have examined important elements of the broader college investment decision including credit constraints (Carneiro and Heckman 2002, Lochner and Monge-Naranjo 2012), information barriers (Bettinger, Long, Oreopoulos and Sanbonmatsu 2012, Hoxby and Turner 2013), learning about one's ability (Stinebrickner and Stinebrickner 2012), and preferences (Cadena and Keys 2015). Our findings demonstrate an additional allocative margin upon which students adjust in response to labor market conditions.[10]

[8] As we discuss in more depth in Section 4, this estimate is conservative in part because it does not adjust for variability in the impact of a recession by major, with lower earning fields hurt both more severely and more persistently than those that typically command higher wages (Oreopoulos et al. 2012, Altonji, Kahn and Speer 2016).

[9] See, for example, Altonji (1993) as well as Cunha, Heckman, Lochner and Masterov's (2006) discussion of the empirical literature in the context of a theoretical framework.

[10] In some cases, parental funding of college may be tied to a student's choice of major, and a strengthening

The result that women are especially responsive to changes in economic conditions in their choice of college majors extends the literature on the gender gap by showing in another setting that women are relatively more responsive to recessions and, further, suggests that this differential responsiveness may reduce the gender gap in affected cohorts (Killingsworth and Heckman 1986, Brown and Corcoran 1997, Turner and Bowen 1999, Blau and Kahn 2007, Gemici and Wiswall 2014). Relatedly, we contribute to the literature on the determinants of STEM majors (Ehrenberg 2010, Arcidiacono, Aucejo and Hotz 2016, Card and Payne 2017). Especially in the case of women, we identify a latent supply of college students with sufficient ability to complete STEM fields. A rise in the unemployment rate encourages more students to pursue STEM majors, which suggests that a substantial fraction of each cohort has sufficient preparation for STEM fields yet chooses alternative majors during periods with stronger labor market prospects. This fact suggests room for policy interventions, although further research would be needed to identify the optimal design. Finally, these findings inform the literature on career choice (Freeman 1976, Oyer 2008, Goldin and Katz 2016) by showing that not only do recessions encourage more college-going and college completion, but that graduates pursue more technical, more career-oriented, and more remunerative fields of study in response to temporary periods of weak labor demand.

The remainder of the paper is organized as follows: Section 2 provides a conceptual framework of the college major decision that directly motivates our primary empirical specification; section 3 describes the data and presents the results on cyclical changes in major choice and the correlates of majors' cyclicality; section 4 estimates how much larger the costs of graduating in a recession would be in the absence of this important adjustment margin; section 5 concludes.

2 Conceptual Framework and Empirical Specification

In this section we present a stylized framework of the college major decision that motivates our empirical specification. We abstract from the choice to enroll in college and instead focus solely on the choice of college major conditional on enrollment.[11] Given our data limitations,

of these ties during downturns could provide a partial explanation of these changing choices. Along a different but related margin, Field (2009) and Rothstein and Rouse (2011) use experimental evidence to show that graduates are responsive to student loan debt burden in their choice of careers.

[11] 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.

we do not explicitly model heterogeneity or uncertainty, but we acknowledge that a richer model with these features would yield a range of interesting testable hypotheses provided a sufficiently detailed dataset.[12]

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 et al. (2012), this utility captures the present discounted value of future earnings and non-pecuniary benefits available to majors. While students gain direct utility from the costs or benefits of investment and coursework, our primary focus is on the *indirect* utility in a modeling sense, as majors can be mapped probabilistically into occupations with differing patterns of expected earnings, employment probabilities, breadth vs. depth of career opportunities, and other characteristics.[13]

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 1960-2011), a number of "structural" (μ_{cm}) factors have also altered the relative utility of different majors. For example, in more recent cohorts, women have faced fewer barriers to completing traditionally "male" 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

[12]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 et al. (2012) on how college students actually form these expectations.

[13]See the relevant extended discussions in Beffy et al. (2012) and Montmarquette et al. (2002).

words, any long-run structural characteristics of a major must change gradually rather than abruptly changing over a business cycle. Empirically, we will 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 trends for men and women over this time period (Gemici and Wiswall 2014).

The cyclical component, γ_{cm}, reflects the fact that certain majors fare differently over the business cycle, including through earnings or employment effects of the recession itself. To begin, we ask whether the unemployment rate has any effect on the distribution of selected majors. This approach allows us to estimate the effect of the unemployment rate semi-parametrically rather than as a function of major characteristics. In practice, we allow for the utility of the major to depend on $\beta_m * unemp_c$.

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 $U_{icm^*} \geq U_{icm}\ \forall m \neq m^*$. Because the unemployment rate is a cohort-level characteristic, in our main specifications we aggregate to cohort-major cells and run linear 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 choice probability ($Pr(m = m^*) \equiv \pi_{cm}$) plus an error term.

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

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 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 $f_m(c) = \delta_{1m}c + \delta_{2m}c^2$, 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 relatively long time dimension of the 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 all of the γ_c are zero for each c. In effect, this assumption implies that the unemployment rate does not alter the average log(share) across all majors. 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. In the Appendix we discuss a test for assessing the validity of this assumption (which the data fail to reject), as well as robustness results using average marginal effects from a multinomial logit specification, and our semi-elasticity approach yields extremely similar results both qualitatively and quantitatively.

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 assumption. Note that we do not need to know the mechanism by which unemployment affects major choice to establish causality. In fact, we would need stronger assumptions (i.e. an exclusion restriction) to determine the effect of potential mechanisms through which cycles could affect major choices, e.g. earnings or employment expectations. Thus, we think of our approach as treating recessions as natural experiments, and determining the extent to which recessions, exogenous from the perspective of contemporaneously enrolled college students, lead to changes in the composition of college majors.

3 Data and Results

3.1 Data Sources and Descriptives

Our empirical analysis takes advantage of field-of-study questions available beginning in the 2009 wave of the American Community Survey.[14] In this roughly one percent 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. By combining data from the five annual surveys from 2009-2013, we are able to calculate the distribution of college majors for cohorts turning age 20 from 1960-2011 based on a roughly five percent random sample of the population. The ACS also includes the respondent's age, which allows us to add age-specific unemployment rates to each record.[15] The initial analysis uses this data source to determine whether and how major choices change over the business cycle.

We then supplement these cyclicality estimates with characteristics of majors calculated from the public use version of a single wave (1993) of the Baccalaureate and Beyond survey (B&B).[16] In order to combine these two data sources, it was necessary to create a standardized list of majors that can be constructed from the underlying coding schemes in both surveys. 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.

3.2 Cyclical Changes in Major Choices

3.2.1 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 model with major (m) $\times$ birth cohort (c) cells as observations, which is motivated by the

[14] We accessed the ACS through the IPUMS web server (Ruggles, Alexander, Genadek, Goeken, Schroeder and Sobek 2010).

[15] We use the annual national unemployment rate, calculated among all persons ages 16 and over: BLS series ID LNU04000000.

[16] 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 that grouped fields according to the categories provided in Appendix Table A-1.

discussion in the previous section.[17] We use the 38 major classifications discussed previously and the 52 birth cohorts that turned 20 years old in the years 1960-2011. All of the analysis is run separately for men and women.

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

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 trends. We report standard errors based on a block-bootstrap procedure that resamples entire cohorts.[18] We also save each of these bootstrap trials for use in subsequent analysis.

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 trends. In the main text, we rely on major-specific quadratic trends, but 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. Panel A shows both the raw log(share) data (the solid line) and the fitted quadratic trends (the dashed line) for Engineering and for Early and Elementary Education from 1960-2011. 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.

The solid lines in Panel B of the figure show the residual changes in log(share) after removing the influence of these major-specific trends. The dashed lines represent a similarly de-trended version of the unemployment rate.[19] 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 +0.13

[17] Nevertheless, we have estimated the corresponding conditional 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 conditional logit are very similar to the linear regression estimates.

[18] We used 5000 bootstrap trials, and the results of this procedure produce qualitatively similar standard errors compared to using cluster robust standard errors clustered at the cohort level.

[19] Specifically, this line shows the residuals from a regression of the unemployment rate on a quadratic trend fit over the same time period.

for Engineering and -0.062 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 thirteen percent and decreases the share of women choosing Early and Elementary Education by a little more than six percent.

3.2.2 Major Cyclicality Results

Figure 3 provides analogous coefficient estimates of the cyclicality of each of the 38 major categories among women. In general, the results are in line with the results from Figure 1, as majors associated with higher salaries tend to gain share while majors associated with lower salaries tend to lose share in response to a one percentage point increase in the unemployment rate. There is also a substantial overall shift in the distribution of major choices over the business cycle: 22 of the 38 majors have an unemployment gradient that is statistically significant at the 0.01 level, and an additional five majors have coefficients that are different from zero at either the 0.05 or 0.10 level.

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. Figure 4 provides corresponding coefficient estimates of Equation 7 using the raw share values as the dependent variable. This alternative specification shows that, in raw selection probability terms, the greatest gain in share occurs in Business fields: A one percentage point increase in the unemployment rate leads to more than 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 decreases the share of women with any Education degree by more than one percentage point (combining the coefficients on the two Education fields).

The results for men are broadly similar, with most majors either gaining or losing share consistently across both gender groups.[20] The semi-elasticity results for men are given in Figure 5 and share estimates are in Figure 6. 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. There are, however, smaller changes overall among men's chosen fields in response to fluctuations in the unemployment rate.

Adding up the absolute value of the coefficients for shares yields 4.1 percentage points in total reallocation among women as opposed to 3.2 percentage points among men.[21] The

[20] Although the point estimates differ in sign for a few majors, there is no category for which both of these point estimates are statistically significantly different from zero. Appendix Table A-4 shows the difference in coefficients, including tests of the differences in elasticities between genders.

[21] The level of these estimated net reallocation effects is naturally sensitive to the number of major cate-

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). Overall, the evidence from these figures 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.

3.3 Correlates of Majors' Cyclicality

The goal of this section is to characterize the time-invariant attributes of college majors that are associated with a major's cyclicality. Put simply, 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 1993 Baccalaureate and Beyond (B&B) survey. Note that this set of specifications is cross-sectional, and we in effect assume that the relative differences in major characteristics are fixed over time. Although this assumption does not need to be strictly true, it must be plausible that students' perceptions of the relative rank ordering of majors does not change substantially over our period of analysis.[22] 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.[23] This division is useful for exploring a range of hypotheses surrounding why certain college majors exhibit greater cyclicality than others.

3.3.1 Bivariate Relationships with Major Cyclicality

We begin with a set 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:

$$\hat{\beta}_m = \phi_0 + \phi_1 * X_m + \omega_m \tag{8}$$

As the dependent variable in this second-stage regression is derived from the earlier

gories. 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.

[22] The results are stable when limiting the analysis to the 1976-present time period. See Appendix Section A-8 for details.

[23] Summary statistics for each of these variables is available in Appendix Table A-5.

"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's from the first stage.[24] Second, in order to conduct inference, we empirically approximate the distribution of the second-stage coefficients (ϕ's) by estimating Equation 8 repeatedly using the set of β coefficients from each of the first-stage bootstrap trials. We report standard errors calculated as the standard deviation of the relevant ϕ coefficient from this distribution.

We first analyze the relationship between cyclical changes in share and the long-run earnings of a major. Figure 7 presents this relationship for women with median wages of prime-age workers on the x-axis and the degree of cyclicality (as estimated above) on the y-axis. Each dot represents a major, and 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 Pharmacy and Engineering) 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.

There are two likely explanations for this phenomenon. Perhaps the most obvious candidate is the heterogeneity in earnings losses experienced by those who graduate in a recession based on their chosen major (Oreopoulos et al. 2012). As shown by Altonji et al. (2016), this heterogeneity is primarily a function of the long-run earnings associated with each major. Graduates who choose majors with lower long-run earnings lose, on average, more of their lifetime income when they graduate in a high unemployment environment. Thus, part of this relationship likely results from students' responses to these differential anticipated losses in earnings.

In addition, the experience of graduating in a time of high unemployment may alter how students collect and consider information about the relative returns to majors. Although students typically have fairly imprecise information about the relative value of different degrees, they may optimally choose to acquire this information during a time of labor market distress. Greater information gathering could also serve to increase the relative utility of majors that lead to higher salaries as students' priors become less diffuse. Each of these

[24] 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).

reasons, therefore, is consistent with the observed re-balancing of the major distribution toward those that tend to have higher earnings.

The corresponding slope coefficient from Figure 7 is presented formally in the first row and first column of Table 1. This statistically significant coefficient implies that each ten percent increase in long-run median wages is associated with a 1.9 log point more positive semi-elasticity with respect to a one percentage point increase in the unemployment rate. For example, Nursing majors earn about twenty percent more than Psychology majors. Majors whose graduates earn in the range of Nursing are expected to see gains in share of roughly 3.3 percent with each one percentage point increase in the unemployment rate. In contrast, majors that pay like Psychology are expected to lose 0.5 percent share with each percentage point rise in unemployment.

The additional entries in Table 1 provide the corresponding coefficients from similar bivariate regressions with the same dependent variable (the major-specific coefficients on the unemployment rate) and alternative explanatory variables. The relationship between major cyclicality and the share of majors working full-time, full-year is shown in row 2. Again, there is a statistically strong, positive relationship between changes in major share during times of high unemployment and the long-run labor market prospects of a major. Taken together with the results in the first row, the 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.

The next results in Table 1 examine the relationship between the cyclical changes in major shares and the short-term benefits and short-term costs associated with each major. Recall that these are intended to be "typical" short-run characteristics of majors, calculated from a single cross-section, and therefore reflect a changing prioritization of these characteristics rather than a response to cyclical changes in the characteristics themselves. We find that both men and women choose majors with higher employment rates one year after graduation, more job interviews, and a higher share of jobs in related fields. Thus, recessions increase the importance that students place on being able to find employment in a related field relatively soon after graduation.

Perhaps relatedly, the results in the third panel on major difficulty suggest that students are willing to exert more effort during school by selecting more challenging majors during recessions. Majors with the most mathematical rigor and least grade inflation (such as Engineering) are most responsive to the business cycle, a pattern that holds for both men and for women. Thus, recessions appear to alter students' willingness to pay short-term costs of additional difficulty and effort while in school to obtain majors with these advantages.

Finally, the last panel of Table 1 explores a number of alternative hypotheses. First, we find that students avoid majors with a high share of women (such as Sociology) during recessions. This pattern holds for both male and female students. This finding is of particular interest for female students given concerns that women likely face barriers to pursuing degrees in male-dominated areas, such as STEM fields.[25]

The fact that women are more likely to choose gender-atypical majors 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.[26] 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. Notably, 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).

In addition, we consider whether high unemployment encourages students to prefer majors that allow for greater career mobility, either across geographic labor markets or across occupations. These options could provide an additional hedge against the risk of graduating in a recession. In the next row of the last panel in Table 1, we find that women are drawn to more geographically mobile majors during recessions, unconditional on labor market prospects (we present multivariate analysis below). Despite the fact that college completion has been shown to causally increase geographic mobility (Malamud and Wozniak 2012),

[25] Ehrenberg (2010) provides an overview of these concerns, and additional articles in the same issue address specific research questions related to the differential persistence across gender in STEM fields.

[26] There is some evidence that women's preferences over job characteristics differ from men's (c.f. 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).

perhaps surprisingly this mobility does not differentially increase during recessions for men. We also find no evidence that male students differentially select majors that provide more potential occupations, as we observe no relationship between major cyclicality and a measure of occupational concentration in that major (based on a Herfindahl–Hirschman Index), while women move into majors with less concentrated occupation options and thus more general sets of skills.[27]

Similarly, we find that students tend to move away from majors that typically lead to graduate school. The final row of the table shows negative point estimates for both men and women, although the coefficient is three times larger for women than men. These estimates suggest that recessions lead to more students choosing majors that are effectively "terminal," i.e. that lead to careers without additional schooling. This perhaps surprising result implies that, although some students "wait out" recessions by attending graduate school (Johnson 2013), this behavior likely does not reflect a forward-looking choice of an undergraduate major that more often leads to graduate school. In sum, we find robust evidence that recessions alter the distribution of completed college majors toward those that have higher labor market returns. Students are more likely to select higher-paying jobs with better long-term employment rates and a higher likelihood of working in a related field relatively soon after graduation.

3.3.2 Multivariate Relationships with Major Cyclicality

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. 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 the differences in career prospects afforded by different majors. Additionally, recessions may increase the value of higher education as a signaling device (Spence 1973), and more difficult majors may gain in market share, even beyond what would be expected given their long-run earnings. In the next set of results, therefore, we run "horse race" regressions to test whether other major characteristics are related to the cyclicality of college majors, conditional on how the recession alters relative long-run wage prospects. Recall from the previous discussion that heterogeneity in earnings losses as a result of recessions derives primarily from the long-run

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

earnings and employment probabilities of a graduate's major. Thus the coefficient on this control includes the direct effect of higher long run earnings on major cyclicality as well as the effect of smaller earnings losses due to a downturn.

Table 2 presents the multivariate results related to labor market prospects for women (columns 1–3) and men (columns 4–6), respectively. Beginning in column 1 of Table 2, it is clear that long-run earnings are quite predictive of cyclical changes in share among women: this single variable explains nearly half of the variation (47%) in majors' cyclicality. The ability to find employment, and to find related employment in particular, are strong independent predictors of cyclical changes in share as well (columns 2 and 3). Each of these variables likely reflects students choosing majors with relatively smaller recession-induced declines in labor market prospects. These four measures of labor market prospects explain over 75% of the overall variation in majors' cyclicality.

Columns 4–6 of Table 2 show parallel results for men. Again, long-run earnings explain a significant portion (39%) of the variation in majors' cyclicality. The ability to find employment within the first year is an especially large and significant correlate of cyclicality for men. Our available measures of long- and short-run earnings prospects and employment probabilities explain nearly 60% of the overall variation in major cyclicality for men.

In Table 3, we show the relationships between major attributes and major cyclicality *conditional* on labor market prospects (the four variables shown in Table 2) for women and men, respectively. This table tests whether any of the previously discussed correlations (shown above in Table 1) remain after controlling for changes in relative labor market returns. Notably, we find that, even conditional on long-run earnings, recessions induce women to choose gender-atypical fields. Women also choose more difficult majors during recessions, even controlling for the fact that more difficult majors typically experience smaller declines in expected earnings. Furthermore, women are more likely to select a major with a career orientation, i.e. one with a greater likelihood of working full-time during prime earnings years. Thus, it is not simply that cyclical majors with higher earnings also happen to be male-dominated, more difficult, and more career oriented, but rather that women have increasing preferences for each of these features conditional on long-run earnings potential.

Men generally exhibit similar patterns of major cyclicality, but the magnitudes of the responsiveness (relative to women) are frequently smaller. Men similarly choose more difficult majors during recessions, majors with a greater likelihood of working full-time, and majors that are more male-dominated. These findings support the view that long-run earnings prospects alone are not a sufficient statistic for understanding the responsiveness of either men's or women's major choices to economic conditions, as we observe relationships that are consistent with increased information gathering as well as the increased value of education as a signaling device during recessions.

3.4 Robustness and Extensions

3.4.1 Age of unemployment rate

In the analysis presented so far, 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 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 the first row of Table 1. We vary the age at which the unemployment rate is measured when calculating major cyclicality (the dependent variable in the regression).[28]

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-3 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, 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.

[28] The results for age 20 do not precisely match those listed 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.

3.4.2 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. Because field of degree is observed (and well defined) only for individuals who have completed their degree, the major distribution can change over the business cycle even if no inframarginal individual changes their mind about what to study.[29] In order to separate the influence of changes in composition from changes in majors among those whose bachelor's degree receipt was independent of the state of the business cycle, we provide additional analysis that adjusts for the composition of observable and 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-6, 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. Nevertheless, we can control for permanent characteristics that may be correlated with degree choices. Specifically, we run regressions that replace the major-specific fixed effects from 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 the unemployment rate affects the racial composition, for example, of a cohort and that there are permanent differences in the majors pursued by different racial groups. 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 college 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 4 presents comparisons resulting from such an exercise. Each alternative specification introduces additional interaction terms that allow for the share of each cohort selecting a given major to depend on the cohort's

[29] There is a substantial literature demonstrating that college entrance and persistence are countercyclical. See for example, Betts and McFarland (1995), Dellas and Sakellaris (2003), and Barr and Turner (2013).

college enrollment or completion rates. Specifically, we alter Equation 7 by interacting the major-specific dummy variables with a cohort-specific variable that measures the share of observations with at least some college (enrollment rates) or with at least a bachelor's degree (completion rates).

Table 4 reports two comparisons between each alternative specification and the baseline results. First, we report the correlation of the 32 major-specific unemployment coefficients with the coefficients reported in Figures 3 and 5. Second, we report the second-stage regression coefficient and R-squared from regressing these coefficients on the long-run earnings of each major (baseline results shown in the first row of Table 1).

For most samples and time periods the results are qualitatively similar whether or not controls for enrollment or completion are included. The exception is the analysis using the entire 1960–2011 time period for men. The results adjusting for enrollment and completion are somewhat different than the baseline results (correlation coefficients of +0.72 and +0.58, respectively), and the relationship between major cyclicality and long-run earnings potential is noticeably weaker (0.05 vs. 0.11). During the early part of this time period however, enrollment and completion were strongly *procyclical*, in contrast to the more recent time period when enrollment and completion are countercyclical. In particular, the Vietnam War years show a noticeable spike in male enrollment and completion concurrent with low unemployment. When we limit the analysis to the 1976–2011 time period, the results with and without the composition adjustments are more comparable.

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.

3.4.3 Local unemployment rates

The analysis presented thus far 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 in their state of birth at age 20. There is not, however, information on where individuals attended school, nor on where they intended to settle following school. In Appendix Tables A-7 and A-8, we provide some analysis using the local unemployment rates for individuals' state of birth (further discussed in Appendix Section A-8).

First, we repeat the analysis from Equation 7 using state-birth year-major cells, replacing the national unemployment rate with the state-specific unemployment rate. These results are qualitatively similar although the magnitudes of the changes in major shares are typically (though not uniformly) smaller. We also estimate a version of Equation 7 that is identified using only the cross-sectional variation around the national business cycle.[30] This specification is extremely demanding of the data, and the results are quite noisy.

Although this specification has the advantage of fully removing the effects of unobserved (constant across states within a year) changes in demand for each major, it comes with the drawback that it explicitly ignores responses to the shared (across space) component of the business cycle. Because labor markets for college educated individuals are more geographically integrated, we interpret the different results at the two levels of geography as indicating that national labor market conditions rather than local deviations around national conditions drive much of individuals' perceptions of the value of different majors.

3.4.4 Wages of marginal individuals

A final extension 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 end up with earnings that are below average. We examine this question in detail in Appendix Section A-9. 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 effects of graduating in a recession (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, the evidence suggests that individuals who choose a different major as a result of the state of the business cycle eventually have earnings similar to the inframarginal graduates with the same major.

[30]This specification uses fully non-parametric major-specific trends (year dummies) rather than assuming that the underlying trends are smooth.

4 Implications for the Analysis of Graduating in a Recession

The previous section established 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 incorporate the impact of this compensating behavior. In this subsection, we use our earlier results to provide an estimate of how much larger the costs of graduating in a recession would be in the absence of this behavior. 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 ($majorval$):

$$log(earnings)_c = \beta_0 + \beta_1 unempgrad_c + \beta_2 majorval_c + \epsilon_c \tag{9}$$

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.[31] 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:

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

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

$$\tilde{\beta_1} = \beta_1 + \beta_2 \frac{Cov(majorval, unempgrad)}{Var(unempgrad)} \tag{11}$$

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

[31] 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.

influence the set of majors selected by a cohort:

$$majorval_c = \gamma_0 + \gamma_1 unempmid_c + \eta_c \quad (12)$$

Again, relying on the assumption that the unemployment rate at graduation is unrelated to the residual in the major value equation, the expression in (11) simplifies to:

$$\tilde{\beta}_1 = \beta_1 + \beta_2\gamma_1\delta_1 \quad (13)$$

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 expect that the first coefficient, β_2, is positive by construction – more valuable majors increase earnings. As the previous results in the paper have shown (including perhaps most directly Figure 1), the sign of γ_1 is also positive, as the typical major-based earnings capacity of a cohort rises in response to unemployment experienced partway through school. The final coefficient, δ_1, is also positive: A regression of the unemployment rate at time t on the unemployment rate at time $t + 2$ over our time period yields a coefficient of +0.43.[32] Thus, the total difference is positive: 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.

4.1 Quantifying the Offset

Determining how much of the overall demand shock from graduating in a recession is offset by changes in the major distribution requires numerical estimates of the first and second regression coefficients in addition to the +0.43 estimate of δ_1. Doing so requires a more

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

exact definition of *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.

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

$$\bar{x_1} - \bar{x_0} = \sum_j (\omega_{j1} - \omega_{j0}) x_j. \quad (14)$$

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, $\bar{x}$.[33]

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 resulting change in the distribution of chosen majors.[34] To obtain the effect of an increase in unemployment at the time of graduation, we scale this coefficient by 0.43, the increase in unemployment at age 20 associated with a one percentage point rise in the unemployment rate at age 22 (δ_1). 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 the cohort graduating with average unemployment.[35]

[33] 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.

[34] 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 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.

[35] This characterization of a "recession" is the same as used in Altonji et al. (2016).

The only remaining component of the calculation is selecting a reasonable value of β_2, the regression coefficient of earnings in a recession on major value. Given that both the major-based earnings capacity variable and the dependent variable are measured as log(earnings), a reasonable benchmark is $\beta_2 = 1$. A coefficient of 1 would imply 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 et al. 2012, Altonji et al. 2016).

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, with our results implying that the demand effect alone is roughly ten percent larger than the combined effect of supply and demand. Thus, even accounting for recession-induced changes to college majors, it seems likely that most students who graduate during a recession experience negative earnings as a result.

In contrast, the results suggest relatively mild earnings effects from experiencing a recession while in school. For example, our results imply that a 3 percentage point rise in unemployment rates at age 20 leads to a distribution of majors that earns roughly 1.5 percent more, on average, on a permanent basis. Because we cannot observe both the chosen and counterfactual major, we are unable to determine for any particular individual how a recession affects her lifetime earnings.[36] Nevertheless, it seems likely that for many students, the presence of a recession does not alter their chosen major. In this case, the estimated increase of 1.5 percent of earnings *on average* reflects substantial heterogeneity between marginal and inframarginal individuals. Among those who choose different majors as a result of the recession, the recession induces a large increase in lifetime earnings, even when accounting for the negative labor demand effect at the time of graduation.[37]

[36] In addition, this is an inherently partial equilibrium estimate, and there may be broader general equilibrium effects, as found in Bianchi's (2014) study of Italian educational reforms.

[37] 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, the average gains among switchers would be larger than the resulting demand shock. Note that each percentage point increase in the unemployment rate at age 20 corresponds with a roughly 0.5 percentage point increase in the unemployment rate at age 22. Thus, the earnings decline due to *graduating* with high unemployment for this cohort would be roughly half of the six to eight percent losses in the literature.

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 1962 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 3.2 percentage point total reallocation of majors for men, and a 4.1 percentage point reallocation for women.

The recession-induced reallocation in college majors shifts the distribution toward fields of study that are more challenging, require more math, and, above all, are higher paying. Long-run earnings in a given major is the strongest predictor of recession-induced reallocation into the field, explaining more than one-third of the variation in cyclical elasticities. Nonetheless, even conditional on long-run earnings we show that students move into more difficult, more male-dominated (among women), and more career-oriented fields. These shifts suggest that a substantial number of college students make an (short- and long-run) earnings-maximizing response to recession conditions by choosing majors that are more insulated from recessions.

We also find that recessions lead to share increases among more difficult and male-dominated majors, even controlling for differences in earnings and the likelihood of finding employment. 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. The stark responsiveness to the business cycle suggests that many college students, and especially female college students, have sufficient ability to complete more challenging majors, such as STEM fields, yet choose not to do so in periods with stronger labor market prospects.[38] A direction for future research is to understand what aspects of the business cycle lead to this adjustment and whether it is possible to encourage

[38]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.

greater take-up of these more difficult fields even in a healthy labor market.

Finally, we use our findings to estimate the quantitative importance of the shift toward more lucrative majors when estimating the impact of graduating in a recession. Relative to the typical estimated impact of graduating in a recession on the order of 6 percent, we find that graduating in a recession would be ten percent more painful had students not reallocated across majors. Relatedly, we find that a three percentage point rise in unemployment at the time of major choice leads to a distribution of majors that earns roughly 1.35 percent more, on average, for their long-run earnings. The results suggest that even brief recessions can have a long-lasting impact on the distribution of human capital in the economy and provide new insight into how labor supply adjusts in meaningful ways to temporary disruptions in labor demand.

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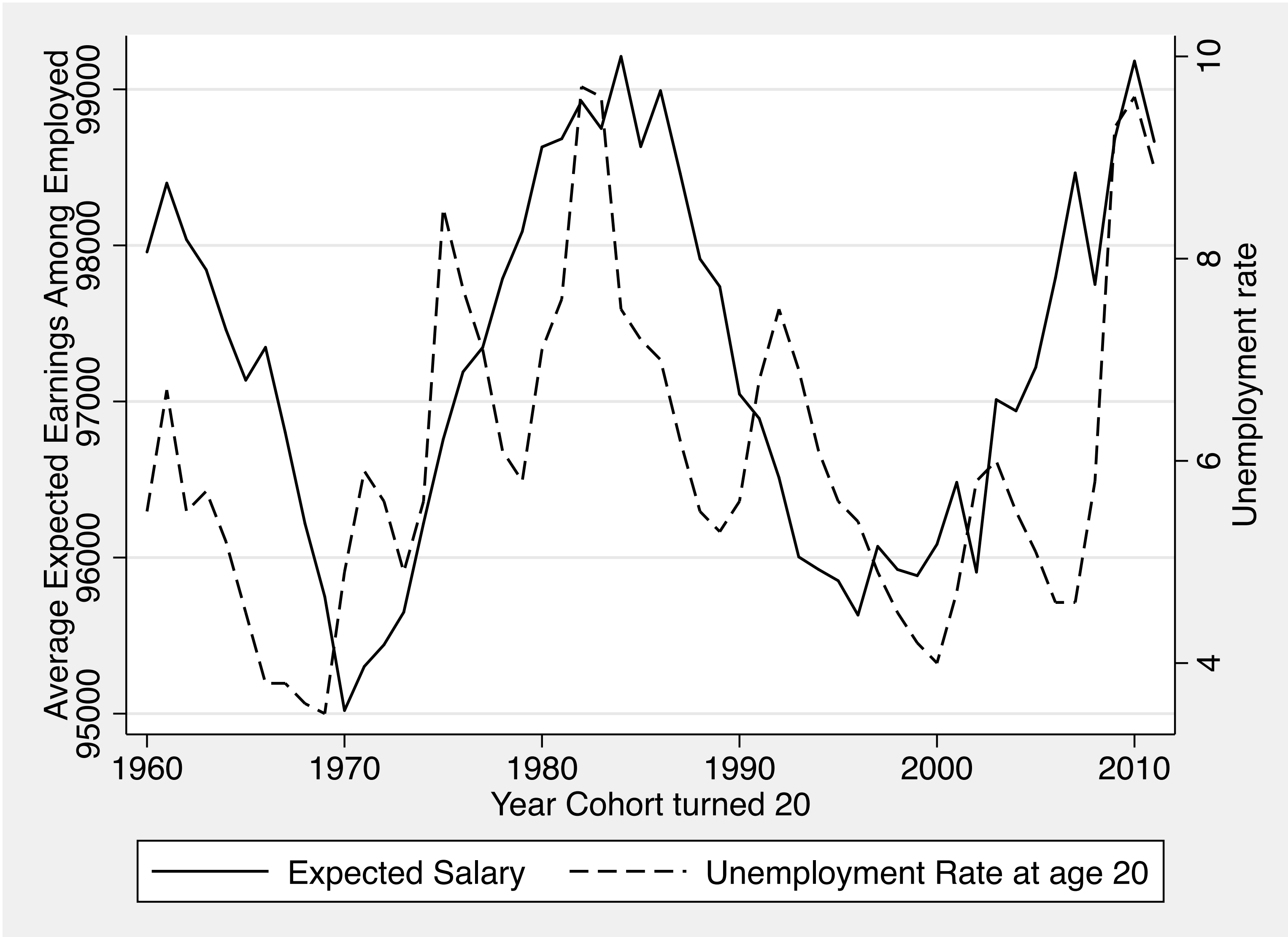
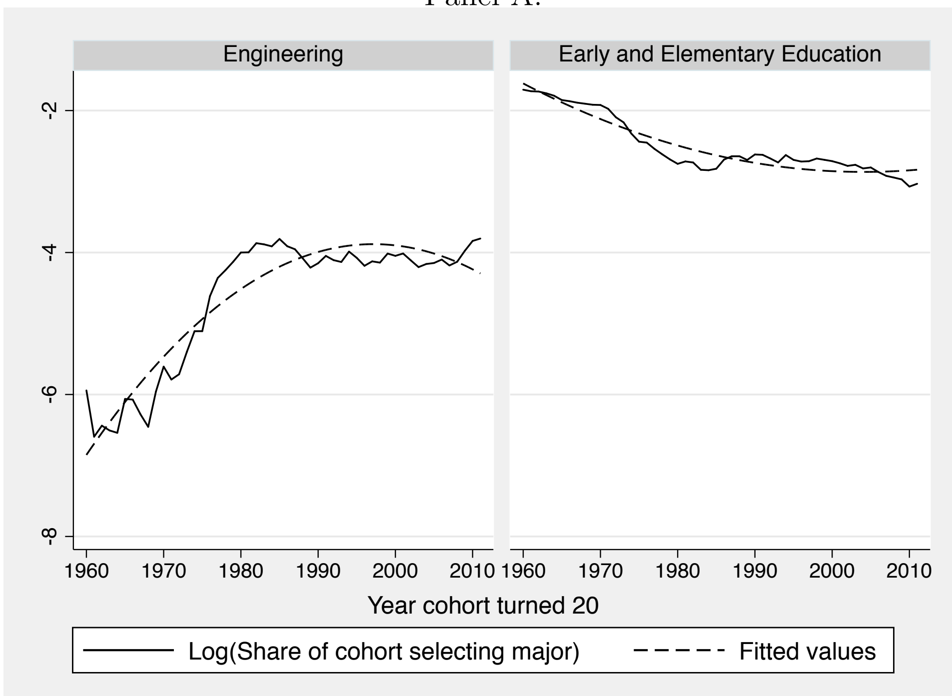
Figure 1: Business Cycles and Average Major-Based Earnings



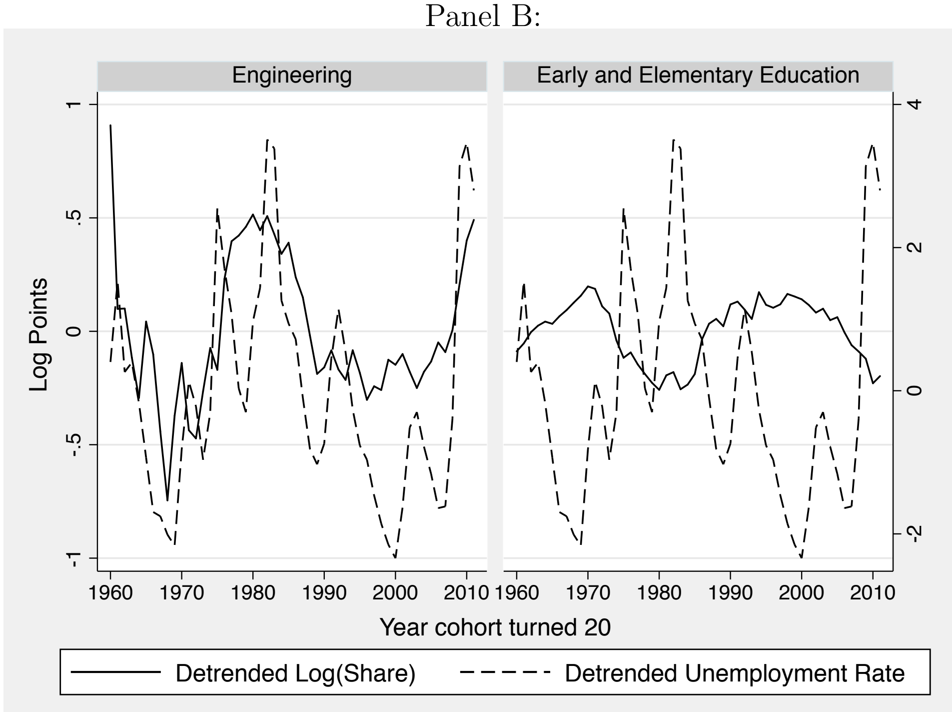
Source: Bureau of Labor Statistics (unemployment rate) and authors' calculations from IPUMS 2009-2012 (average expected earnings). Average expected earnings for a field of study are based on 2009-2012 earnings data among men ages 35-45 who are employed full time (at least 35 hours per week), full year (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: Example of Identifying Variation

Panel A:

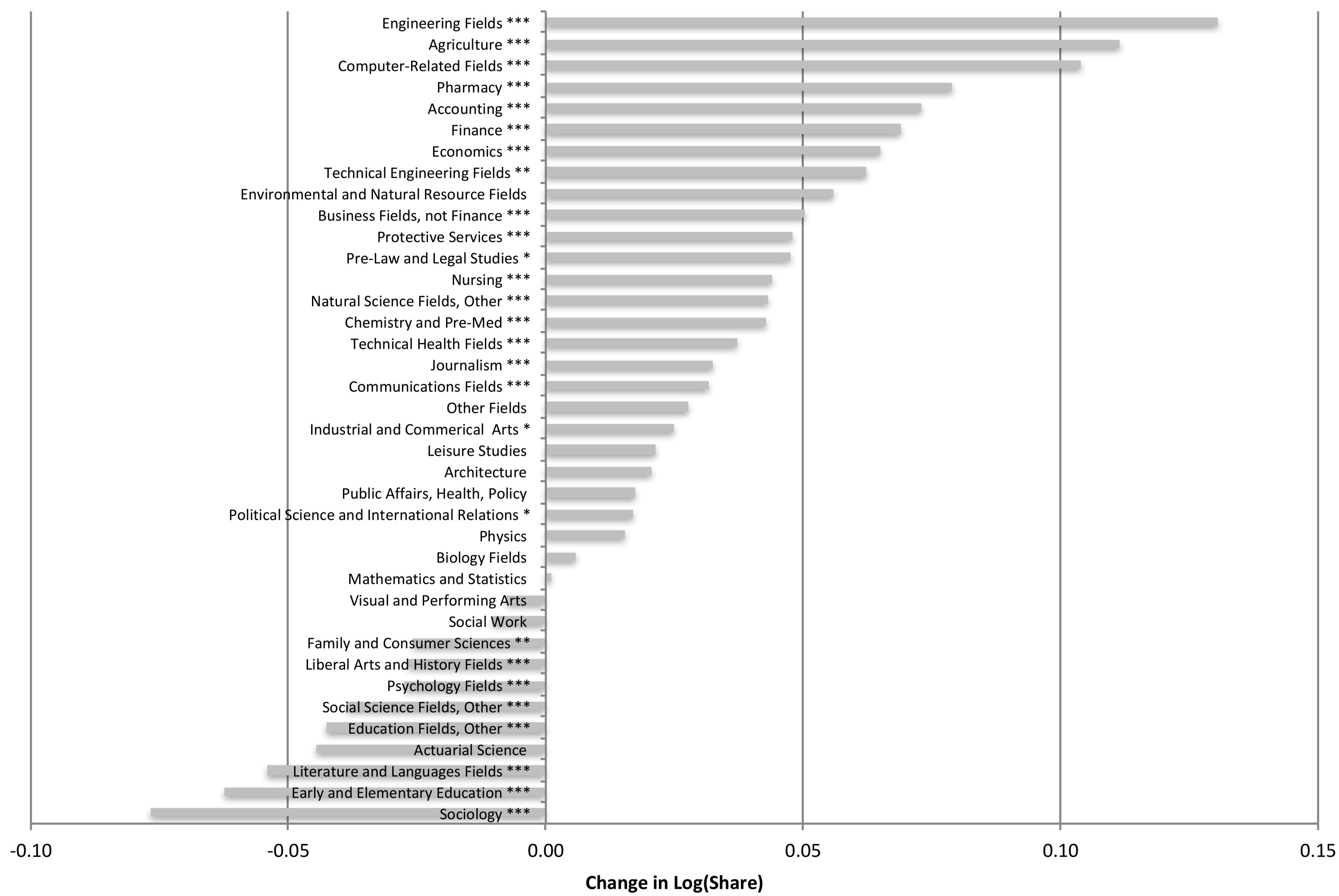


Panel B:



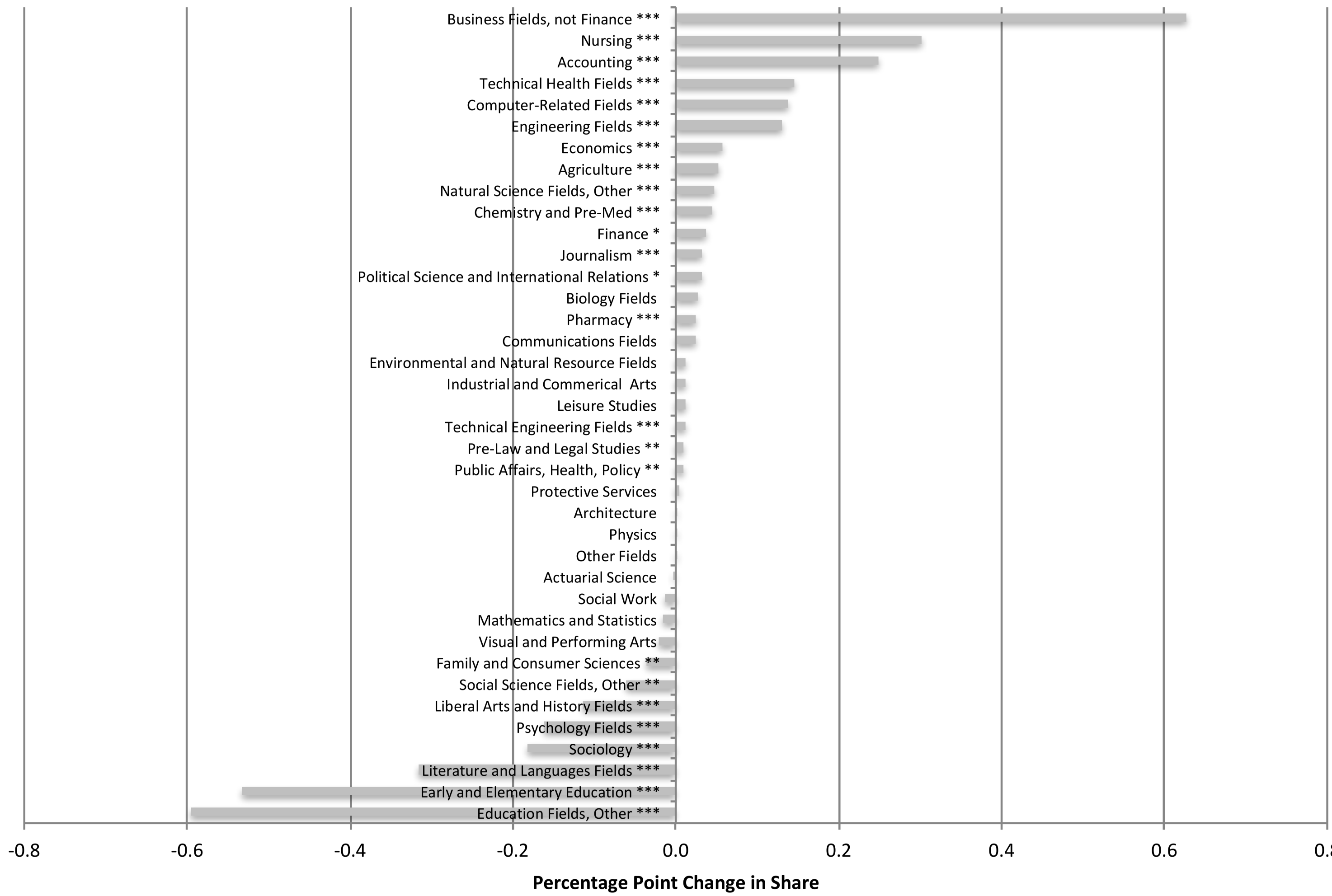
Data sources: BLS and authors' calculations from 2009-2012 ACS data. This analysis is based on the fields of study for birth cohorts of women who completed college degrees. Panel A shows the raw data and best fit quadratic trends for the log(share) of graduates completing degrees in Engineering and Early and Elementary Education. Panel B shows 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



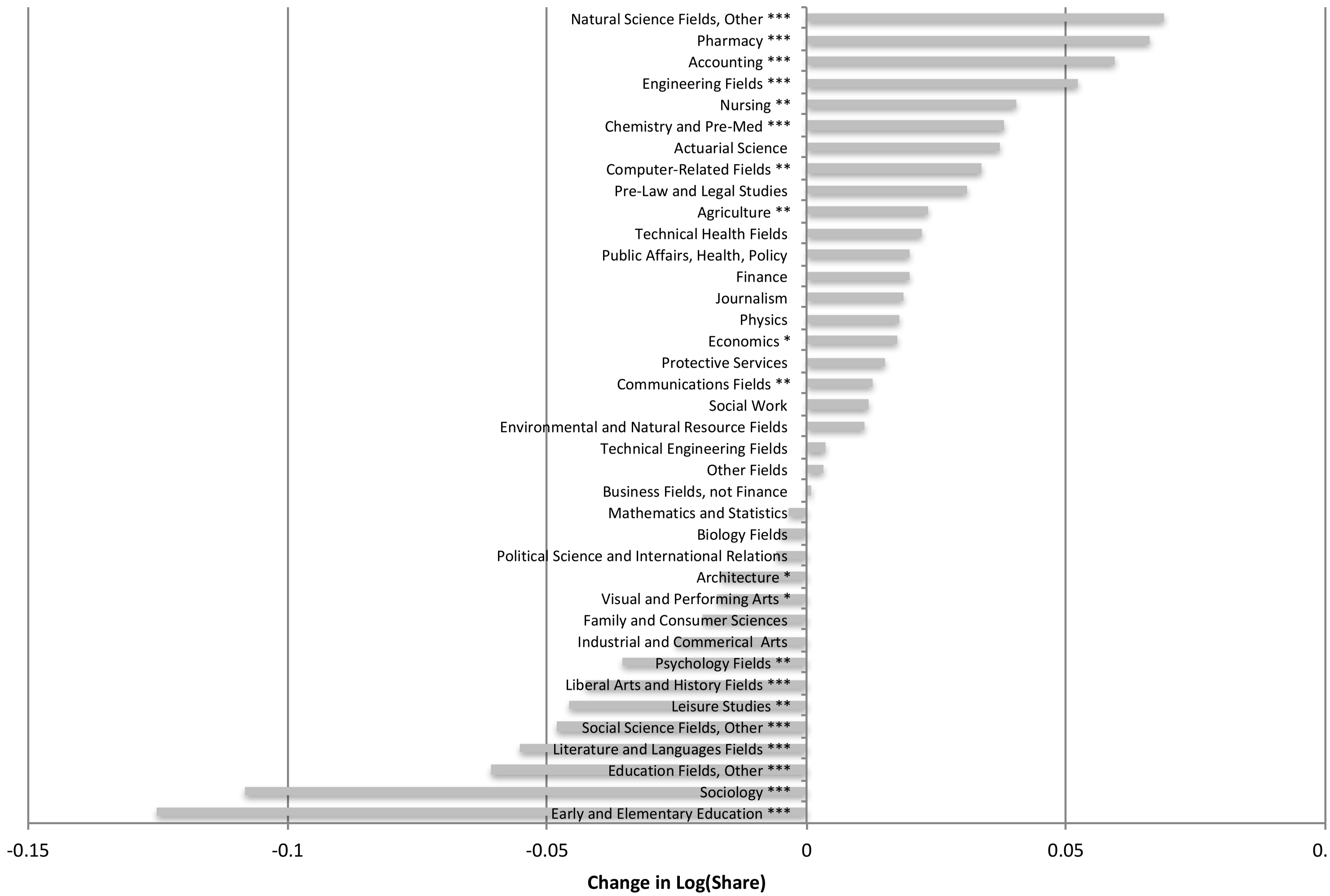
Data sources: BLS and authors' calculations from 2009-2012 ACS data. These coefficients represent the change in log(share) of a birth cohort selecting a given major category due to a one percentage point increase in the unemployment rate and are based on Equation 7, which includes major fixed effects and major-specific trends. Stars next to the name of the 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. The specifications are run separately for men and women; see Figure 5 for the corresponding results for men. 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 Share Due to 1 ppt Increase in Unemployment Rate - Women



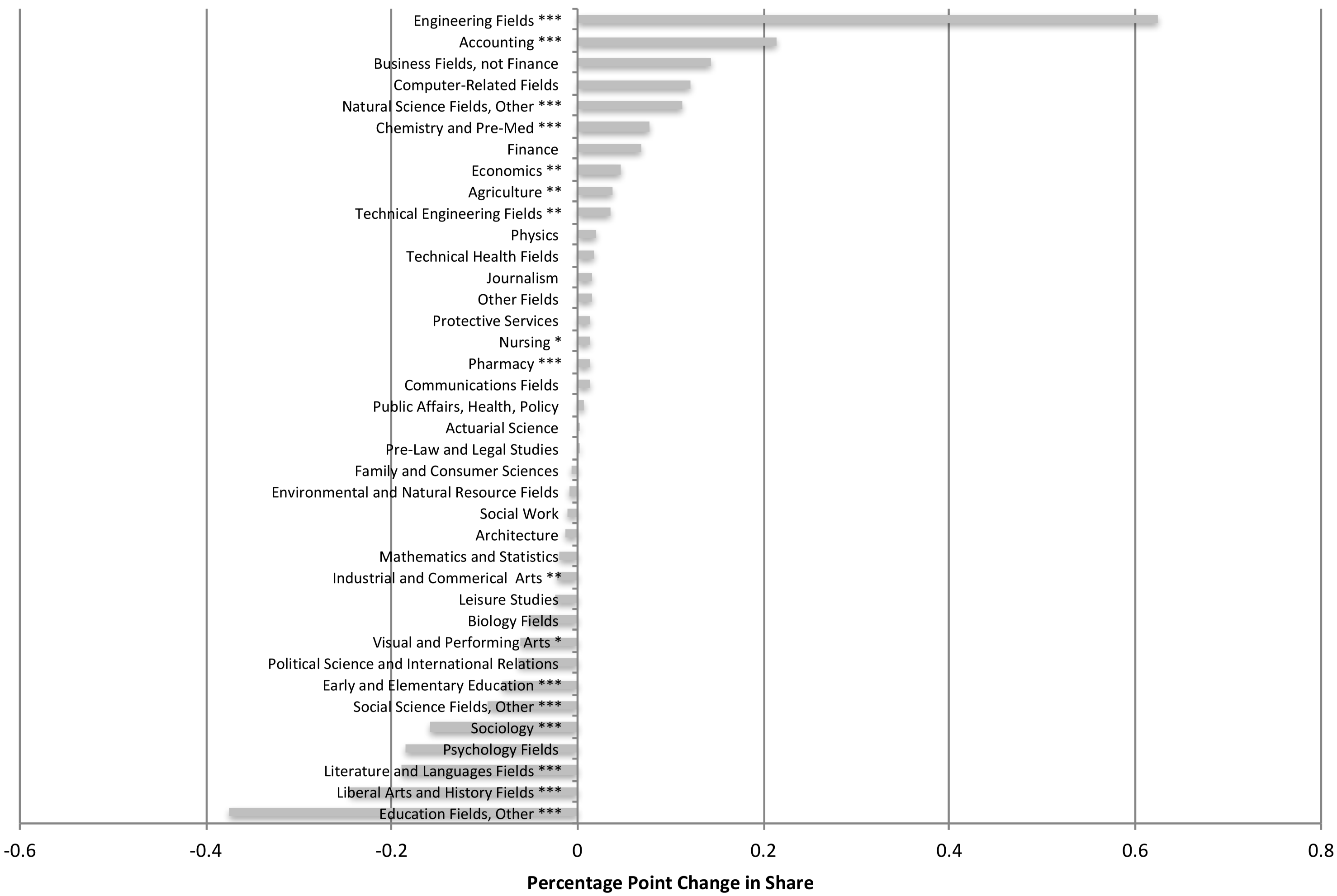
Data sources: BLS and authors' calculations from 2009-2012 ACS data. These coefficients represent the change in share of a birth cohort selecting a given major category due to a one percentage point increase in the unemployment rate and are based on Equation 7, which includes major fixed effects and major-specific trends. Stars next to the name of the 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. The specifications are run separately for men and women; see Figure 6 for the corresponding results for men. 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 Log(Share) Due to 1 ppt Increase in Unemployment Rate - Men



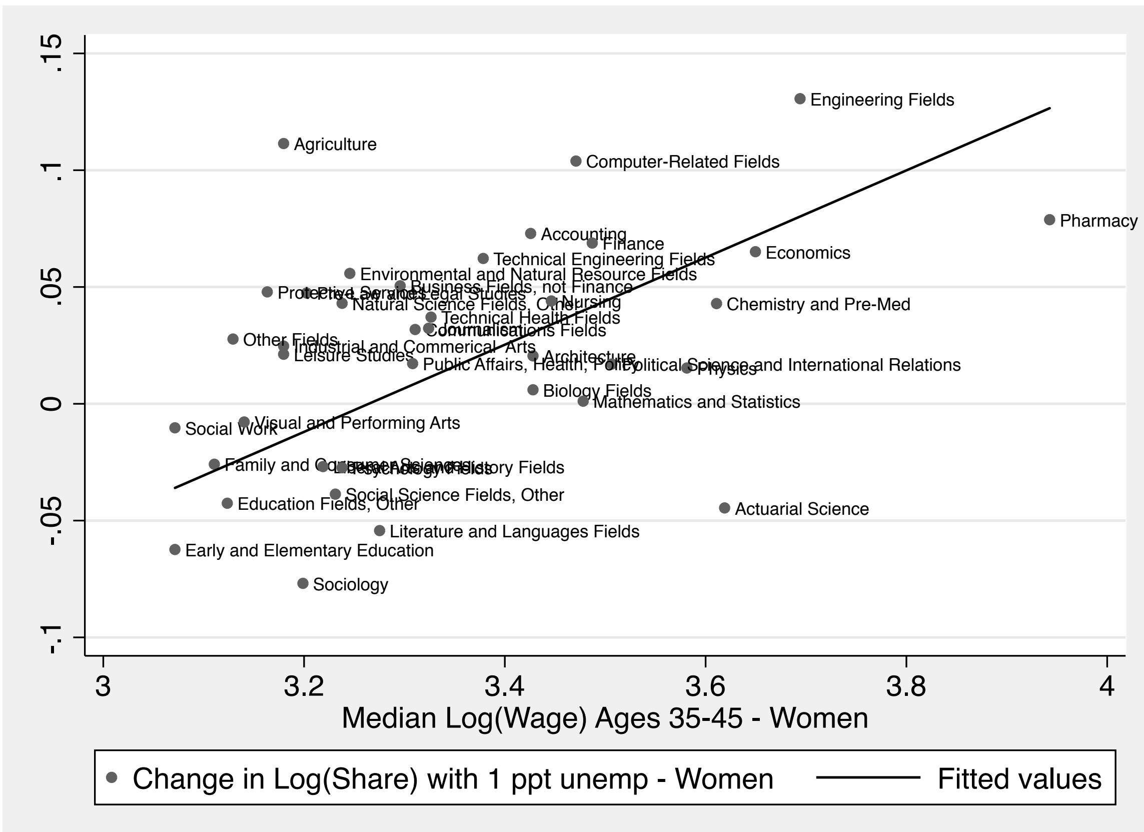
Data sources: BLS and authors' calculations from 2009-2012 ACS data. These coefficients represent the change in log(share) of a birth cohort selecting a given major category due to a one percentage point increase in the unemployment rate and are based on Equation 7, which includes major fixed effects and major-specific trends. Stars next to the name of the 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. The specifications are run separately for men and women; see Figure 3 for the corresponding results for women. 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



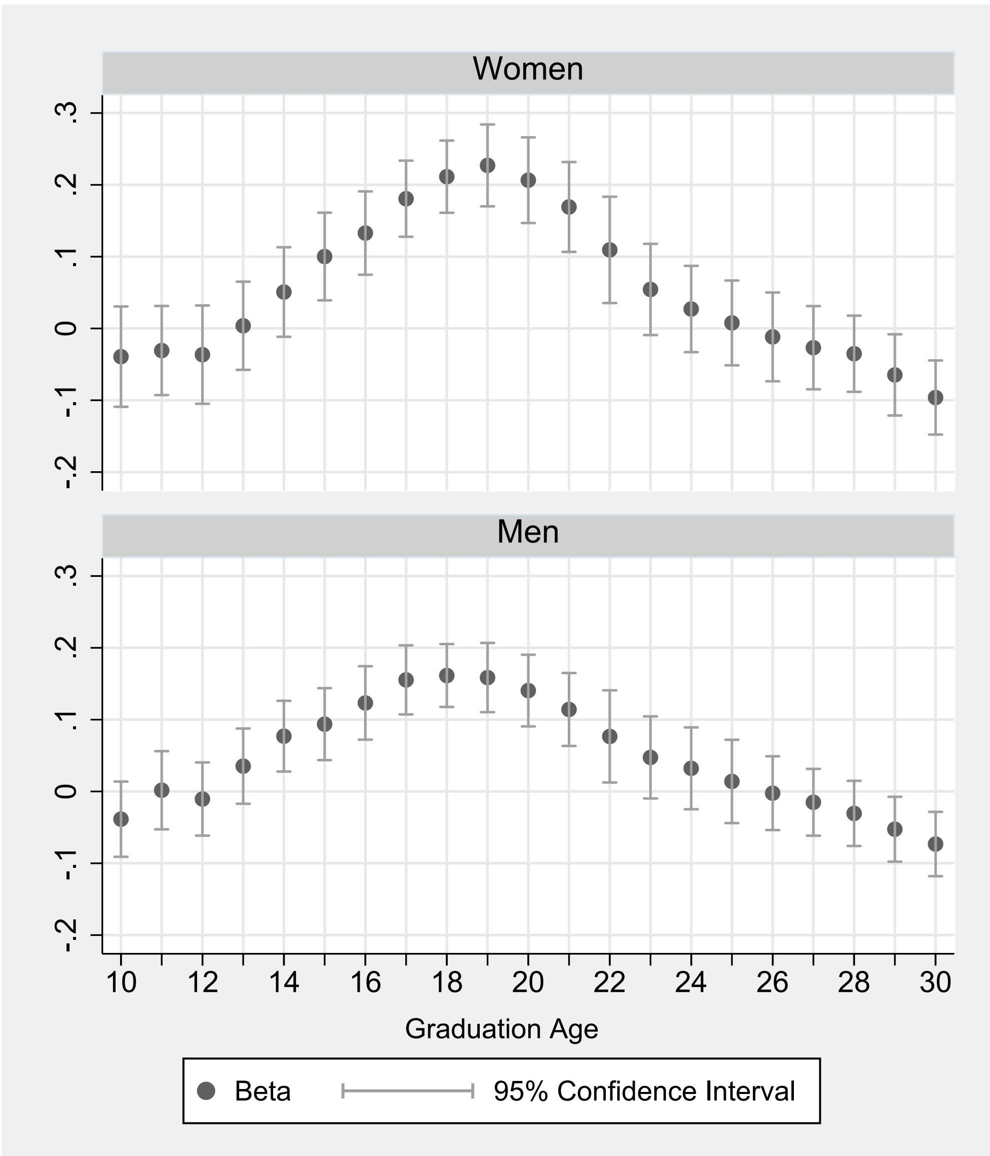
Data sources: BLS and authors' calculations from 2009-2012 ACS data. These coefficients represent the change in share of a birth cohort selecting a given major category due to a one percentage point increase in the unemployment rate and are based on Equation 7, which includes major fixed effects and major-specific trends. Stars next to the name of the 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. The specifications are run separately for men and women; see Figure 4 for the corresponding results for women. 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 an 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 2009-2012.

Figure 8: Median Log Share Second Stage Regression by Graduation Age



The figure plots coefficient estimates from the second stage analysis, 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 included the cohorts born in 1960-1986 as opposed to the original sample of the 1960–1991 birth cohorts so that every cohort in the sample has corresponding unemployment rates for graduation year specification (10-20).

Table 1: Correlates of Cyclical Changes in Major Shares

Characteristic of Major	Women			Men		
Labor Market Prospects - Long Run						
Median Log(Wage) Ages 35-45	0.187	***	(0.023)	0.138	***	(0.020)
Share Working FTFY (35-45)	0.489	***	(0.051)	0.547	***	(0.061)
Labor Market Prospects - Short Run						
Number of Job Interviews w/in first year	0.015	***	(0.002)	0.011	***	(0.003)
Share Employed at 1 year	0.361	***	(0.055)	0.127	***	(0.038)
Share in Unrelated Jobs in first year	-0.166	***	(0.020)	-0.142	***	(0.017)
Difficulty						
Median SAT Math Score/100	0.045	***	(0.005)	0.033	***	(0.004)
Average Math GPA	0.037	***	(0.006)	0.047	***	(0.007)
Average GPA for Major Courses	-0.323	***	(0.038)	-0.191	***	(0.027)
Other						
Long-run average Female Share of Major	-0.117	***	(0.015)	-0.091	***	(0.023)
Share living in state of birth (Age 35-45)	-0.113	***	(0.021)	-0.027		(0.027)
HHI of occupations (Age 35-45)	-0.068	***	(0.010)	-0.004		(0.026)
Share with a grad degree (Age 35-45)	-0.177	***	(0.025)	-0.051	***	(0.017)

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 5. 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-5 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 2: Correlates of Cyclical Changes in Major Shares – Multivariate Analysis of Labor Market Prospects

	Women			Men		
	(1)	(2)	(3)	(4)	(5)	(6)
Median Log(Wage) Ages 35-45	0.203 ***	0.171 ***	0.108 ***	0.145 ***	0.129 ***	0.099 ***
	(0.023)	(0.017)	(0.014)	(0.020)	(0.015)	(0.019)
Number of Job Interviews w/in first year		0.007 ***	0.011 ***		0.004	0.002
		(0.003)	(0.003)		(0.003)	(0.003)
Share Employed at 1 year			0.099 ***			0.2 ***
			(0.034)			(0.041)
Share in Unrelated Jobs in first year			-0.151 ***			-0.123 ***
			(0.021)			(0.019)
Observations	32	32	32	32	32	32
R-squared	0.474	0.523	0.762	0.388	0.406	0.598

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 Figure 3 and 5. 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-5 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: Correlates of Cyclical Changes in Major Shares *Conditional* on Labor Market Prospects

Characteristic of Major	Women			Men		
Labor Market Prospects - Long Run						
Share Working FTFY (35-45)	0.183	***	(0.037)	0.166	***	(0.061)
Difficulty						
Median SAT Math Score/100	-0.011	**	(0.005)	-0.010	**	(0.004)
Average Math GPA	-0.030	***	(0.007)	-0.051	***	(0.008)
Average GPA for Major Courses	-0.180	***	(0.032)	-0.119	***	(0.022)
Other						
Long-run average Female Share of Major	-0.092	***	(0.018)	-0.054	***	(0.017)
Share living in state of birth (Age 35-45)	0.040		(0.038)	0.031		(0.036)
HHI of occupations (Age 35-45)	-0.047	*	(0.026)	-0.059	***	(0.020)
Share with a grad degree (Age 35-45)	-0.143	***	(0.019)	-0.070	***	(0.022)

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 Figure 3 and 5. 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-5 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 4: Second Stage Analysis with Cohort Enrollment and Completion

	Baseline	Non-Parametric with Bandwidth=7		
	(1)	(2)	(3)	(4)
Panel A: Women				
1960-2011				
Correlation with Baseline Beta	1	0.9392	0.9227	0.8148
Coefficients on Median Log Wage	0.1866	0.1403	0.1383	0.1144
R-squared	0.4589	0.4917	0.3575	0.2698
1976-2011				
Correlation with Baseline Beta	1	0.7155	0.7535	0.7621
Coefficients on Median Log Wage	0.1210	0.0949	0.0841	0.0733
R-squared	0.4922	0.5688	0.4584	0.3292
Panel B: Men				
1960-2011				
Correlation with Baseline Beta	1	0.9499	0.7157	0.5785
Coefficients on Median Log Wage	0.1378	0.1133	0.0473	0.0471
R-Squared	0.3791	0.3828	0.1078	0.1559
1976-2011				
Correlation with Baseline Beta	1	0.9254	0.8827	0.8729
Coefficients on Median Log Wage	0.1026	0.1091	0.0868	0.0669
R-Squared	0.4863	0.4047	0.3566	0.2608
Control for Enrollment Rates	N	N	Y	N
Control for Completion Rates	N	N	N	Y

Authors' calculations from ACS and B&B data.

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.

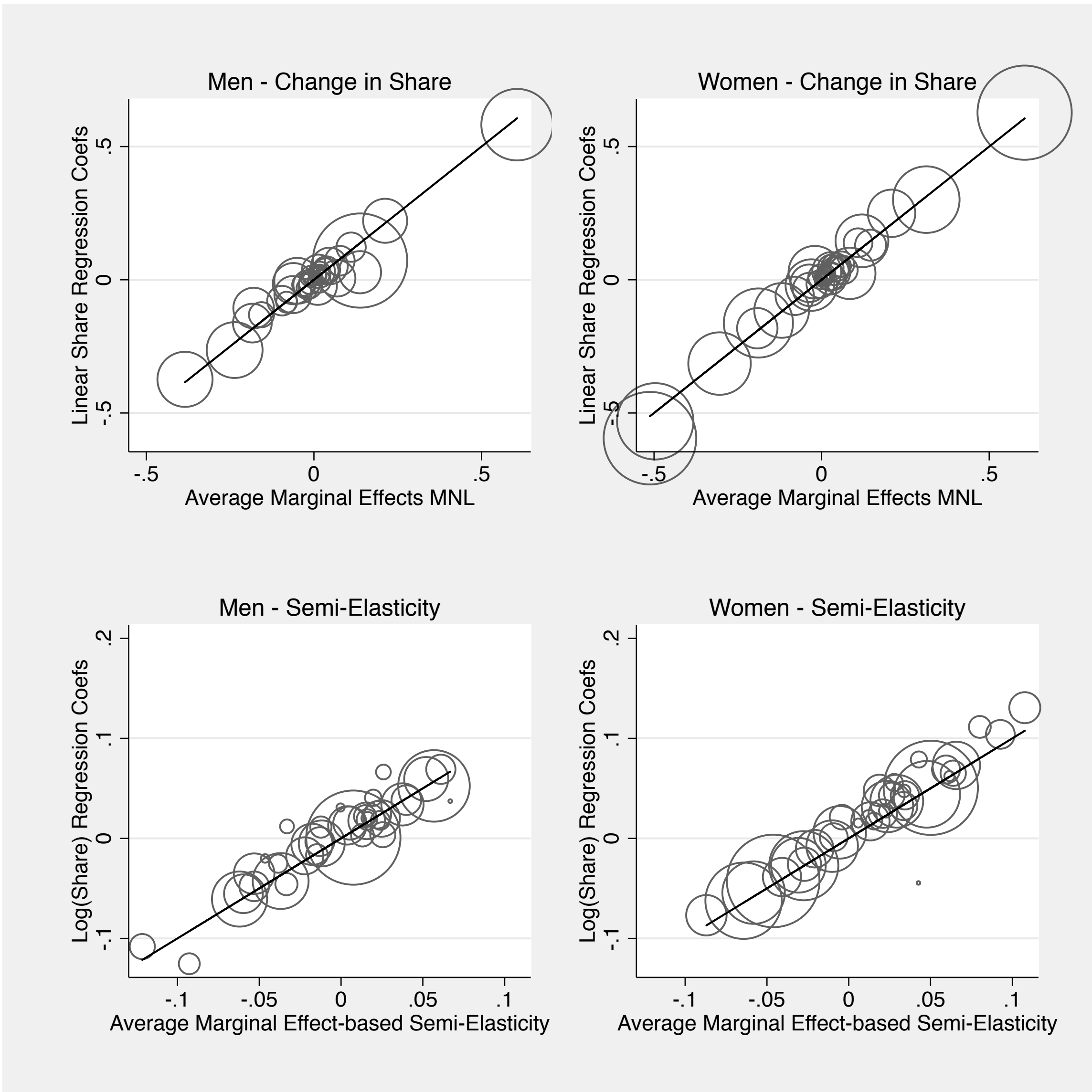
A-2 Major-Specific Time Trends - Robustness

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 Figure A-2 replicates this figure to present a sensitivity analysis of this choice of time trend. 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-2 show three non-parametric alternatives, with bandwidths of 5, 7, and 9 years, respectively, to isolate trends that are slower-moving that most business cycles. Not surprisingly, as the bandwidth is reduces, we observe a closer fit to the overall trend for both engineering and early/elementary education majors.

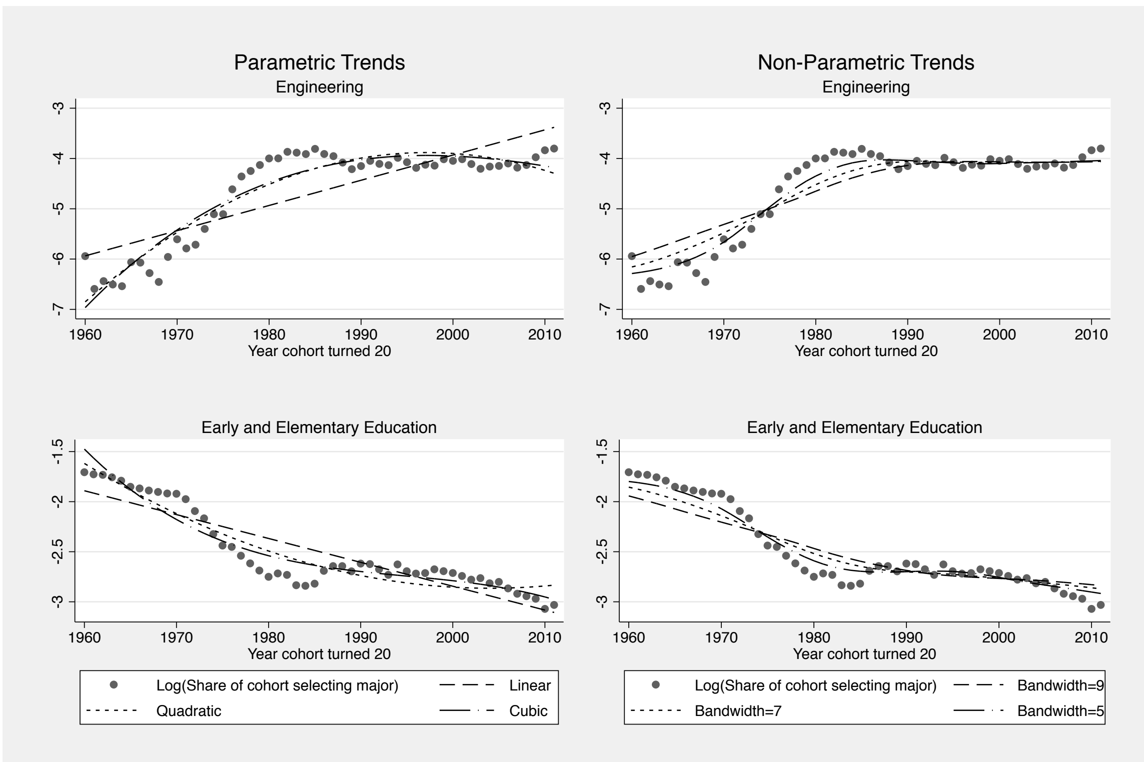
Appendix Table A-2 formalizes this sensitivity analysis across all 38 majors in both the log-share (panel A) and share (panel B) regressions. The sample is of women with bachelor's degrees, and the quadratic time trend is the baseline used in the main text. The explanatory power of each specification 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 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: Major-Specific Time Trend Comparison



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

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	0.3375	0.5677	0.8091	–	0.9877
Quadratic	0.6070	0.8144	0.8824	–	1
Cubic	0.6324	0.8479	0.8953	–	0.9624
Non-parametric					
bw: 9 years	0.5387	0.6925	0.8199	–	0.9804
bw: 7 years	0.6608	0.7987	0.8794	–	0.9392
bw: 5 years	0.7567	0.8785	0.9324	–	0.7673
Panel B: share regressions					
Parametric					
Linear	0.2934	0.5493	0.8495	5.0440	
Quadratic	0.6283	0.7641	0.8588	4.0947	0.9965
Cubic	0.6568	0.7806	0.8657	4.1726	1
Non-parametric					0.9838
bw: 9 years	0.5338	0.6618	0.7959	4.1038	
bw: 7 years	0.6283	0.7641	0.8588	2.8575	0.9878
bw: 5 years	0.7639	0.8552	0.9131	1.6549	0.9606

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	0.0729***	(0.0083)	0.2492***	(0.0336)	0.0320	0.0593***	(0.0107)	0.2213***	(0.0385)	0.0405
Actuarial Science	-0.0446	(0.0806)	-0.0006	(0.0010)	0.0002	0.0372	(0.0551)	0.0026	(0.0018)	0.0003
Agriculture	0.1114***	(0.0283)	0.0519***	(0.0161)	0.0068	0.0235**	(0.0114)	0.0364**	(0.0157)	0.0156
Architecture	0.0205	(0.0174)	0.0029	(0.0052)	0.0035	-0.0167*	(0.0092)	-0.0129	(0.0080)	0.0098
Biology Fields	0.0060	(0.0095)	0.0283	(0.0346)	0.0392	-0.0051	(0.0147)	-0.0039	(0.0661)	0.0440
Business Fields, not Finance	0.0505***	(0.0090)	0.6270***	(0.1415)	0.1261	0.0007	(0.0066)	0.0720	(0.1087)	0.1853
Chemistry and Pre-Med	0.0429***	(0.0113)	0.0452***	(0.0101)	0.0094	0.0382***	(0.0072)	0.0714***	(0.0149)	0.0185
Communications Fields	0.0318***	(0.0096)	0.0240	(0.0389)	0.0375	0.0129**	(0.0063)	-0.0224	(0.0235)	0.0307
Computer-Related Fields	0.1039***	(0.0224)	0.1389***	(0.0349)	0.0118	0.0339**	(0.0134)	0.0282	(0.0817)	0.0372
Early and Elementary Education	-0.0624***	(0.0061)	-0.5314***	(0.0542)	0.0829	-0.1254***	(0.0225)	-0.0843***	(0.0127)	0.0091
Economics	0.0651***	(0.0148)	0.0585***	(0.0133)	0.0091	0.0175*	(0.0090)	0.0515**	(0.0257)	0.0281
Education Fields, Other	-0.0426***	(0.0061)	-0.5946***	(0.0849)	0.1219	-0.0607***	(0.0086)	-0.3738***	(0.0495)	0.0634
Engineering Fields	0.1306***	(0.0204)	0.1297***	(0.0250)	0.0137	0.0524***	(0.0096)	0.5820***	(0.1095)	0.1069
Environmental and Natural Resource Fields	0.0558	(0.0355)	0.0130	(0.0109)	0.0042	0.0113	(0.0241)	0.0123	(0.0225)	0.0094
Family and Consumer Sciences	-0.0259**	(0.0111)	-0.0364**	(0.0180)	0.0158	-0.0201	(0.0212)	-0.0031	(0.0035)	0.0015
Finance	0.0688***	(0.0196)	0.0368*	(0.0220)	0.0111	0.0199	(0.0160)	0.0056	(0.0470)	0.0279
Industrial and Commercial Arts	0.0247*	(0.0137)	0.0123	(0.0189)	0.0116	-0.0253	(0.0194)	-0.0306**	(0.0142)	0.0070
Journalism	0.0323***	(0.0113)	0.0325***	(0.0124)	0.0112	0.0188	(0.0130)	0.0183	(0.0113)	0.0088
Leisure Studies	0.0212	(0.0143)	0.0110	(0.0104)	0.0086	-0.0458**	(0.0184)	-0.0188	(0.0174)	0.0103
Liberal Arts and History Fields	-0.0269***	(0.0053)	-0.1152***	(0.0229)	0.0426	-0.0427***	(0.0071)	-0.2639***	(0.0400)	0.0652
Literature and Languages Fields	-0.0543***	(0.0097)	-0.3146***	(0.0576)	0.0555	-0.0554***	(0.0081)	-0.1628***	(0.0240)	0.0313
Mathematics and Statistics	0.0011	(0.0138)	-0.0162	(0.0162)	0.0110	-0.0033	(0.0087)	-0.0184	(0.0160)	0.0175
Natural Science Fields, Other	0.0430***	(0.0083)	0.0465***	(0.0098)	0.0114	0.0690***	(0.0092)	0.1224***	(0.0162)	0.0179
Nursing	0.0440***	(0.0096)	0.3007***	(0.0692)	0.0631	0.0405**	(0.0169)	0.0147*	(0.0083)	0.0056
Other Fields	0.0277	(0.0261)	0.0021	(0.0067)	0.0027	0.0032	(0.0131)	-0.0058	(0.0165)	0.0108
Pharmacy	0.0788***	(0.0199)	0.0244***	(0.0064)	0.0037	0.0663***	(0.0234)	0.0196***	(0.0074)	0.0045
Physics	0.0153	(0.0205)	0.0026	(0.0026)	0.0011	0.0180	(0.0211)	0.0183	(0.0180)	0.0075
Political Science and International Relations	0.0170*	(0.0090)	0.0319*	(0.0171)	0.0207	-0.0060	(0.0127)	-0.0146	(0.0455)	0.0355
Pre-Law and Legal Studies	0.0474*	(0.0242)	0.0094**	(0.0047)	0.0022	0.0308	(0.0283)	0.0070	(0.0054)	0.0014
Protective Services	0.0479***	(0.0156)	0.0034	(0.0157)	0.0141	0.0153	(0.0131)	0.0320	(0.0388)	0.0230
Psychology Fields	-0.0274***	(0.0078)	-0.1624***	(0.0497)	0.0680	-0.0354**	(0.0178)	-0.1062	(0.0648)	0.0344
Public Affairs, Health, Policy	0.0172	(0.0112)	0.0084**	(0.0040)	0.0040	0.0200	(0.0182)	0.0059	(0.0059)	0.0034
Social Science Fields, Other	-0.0387***	(0.0132)	-0.0605**	(0.0252)	0.0209	-0.0480***	(0.0123)	-0.0784***	(0.0199)	0.0184
Social Work	-0.0103	(0.0128)	-0.0135	(0.0246)	0.0201	0.0119	(0.0320)	0.0052	(0.0114)	0.0040
Sociology	-0.0769***	(0.0154)	-0.1820***	(0.0385)	0.0232	-0.1082***	(0.0201)	-0.1312***	(0.0257)	0.0132
Technical Engineering Fields	0.0622**	(0.0290)	0.0107***	(0.0031)	0.0015	0.0036	(0.0141)	0.0335**	(0.0145)	0.0131
Technical Health Fields	0.0371***	(0.0094)	0.1460***	(0.0375)	0.0396	0.0221	(0.0179)	0.0264	(0.0183)	0.0102
Visual and Performing Arts	-0.0078	(0.0095)	-0.0201	(0.0367)	0.0378	-0.0175*	(0.0099)	-0.0557*	(0.0286)	0.0287

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.

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	0.0593	***	0.0729	***	0.0136		(0.0129)
Actuarial Science	0.0372		-0.0446		-0.0818		(0.1063)
Agriculture	0.0235	**	0.1114	***	0.0879	***	(0.0243)
Architecture	-0.0167	*	0.0205		0.0372	**	(0.0186)
Biology Fields	-0.0051		0.0060		0.0111		(0.0118)
Business Fields, not Finance	0.0007		0.0505	***	0.0498	***	(0.0072)
Chemistry and Pre-Med	0.0382	***	0.0429	***	0.0048		(0.0118)
Communications Fields	0.0129	**	0.0318	***	0.0190	*	(0.0101)
Computer-Related Fields	0.0339	**	0.1039	***	0.0700	***	(0.0177)
Early and Elementary Education	-0.1254	***	-0.0624	***	0.0630	***	(0.0197)
Economics	0.0175	*	0.0651	***	0.0476	***	(0.0150)
Education Fields, Other	-0.0607	***	-0.0426	***	0.0181	***	(0.0051)
Engineering Fields	0.0524	***	0.1306	***	0.0782	***	(0.0138)
Environmental and Natural Resource Fields	0.0113		0.0558		0.0444	*	(0.0253)
Family and Consumer Sciences	-0.0201		-0.0259	**	-0.0058		(0.0236)
Finance	0.0199		0.0688	***	0.0490	***	(0.0132)
Industrial and Commercial Arts	-0.0253		0.0247	*	0.0501	***	(0.0187)
Journalism	0.0188		0.0323	***	0.0135		(0.0136)
Leisure Studies	-0.0458	**	0.0212		0.0669	***	(0.0178)
Liberal Arts and History Fields	-0.0427	***	-0.0269	***	0.0158	*	(0.0091)
Literature and Languages Fields	-0.0554	***	-0.0543	***	0.0011		(0.0072)
Mathematics and Statistics	-0.0033		0.0011		0.0044		(0.0105)
Natural Science Fields, Other	0.0690	***	0.0430	***	-0.0260	**	(0.0121)
Nursing	0.0405	**	0.0440	***	0.0035		(0.0163)
Other Fields	0.0032		0.0277		0.0245		(0.0317)
Pharmacy	0.0663	***	0.0788	***	0.0125		(0.0206)
Physics	0.0180		0.0153		-0.0027		(0.0296)
Political Science and International Relations	-0.0060		0.0170	*	0.0230		(0.0143)
Pre-Law and Legal Studies	0.0308		0.0474	*	0.0166		(0.0269)
Protective Services	0.0153		0.0479	***	0.0326	*	(0.0181)
Psychology Fields	-0.0354	**	-0.0274	***	0.0080		(0.0143)
Public Affairs, Health, Policy	0.0200		0.0172		-0.0028		(0.0237)
Social Science Fields, Other	-0.0480	***	-0.0387	***	0.0093		(0.0084)
Social Work	0.0119		-0.0103		-0.0222		(0.0229)
Sociology	-0.1082	***	-0.0769	***	0.0313	**	(0.0148)
Technical Engineering Fields	0.0036		0.0622	**	0.0586	**	(0.0256)
Technical Health Fields	0.0221		0.0371	***	0.0149		(0.0163)
Visual and Performing Arts	-0.0175	*	-0.0078		0.0097		(0.0090)

A-5 Descriptive Statistics for Correlates of Major Cyclicality

Table A-5 provides descriptives statistics for the major-specific characteristics used in the analysis in section 3.3 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-5: Descriptive Statistics for Correlates of Major Cyclicality

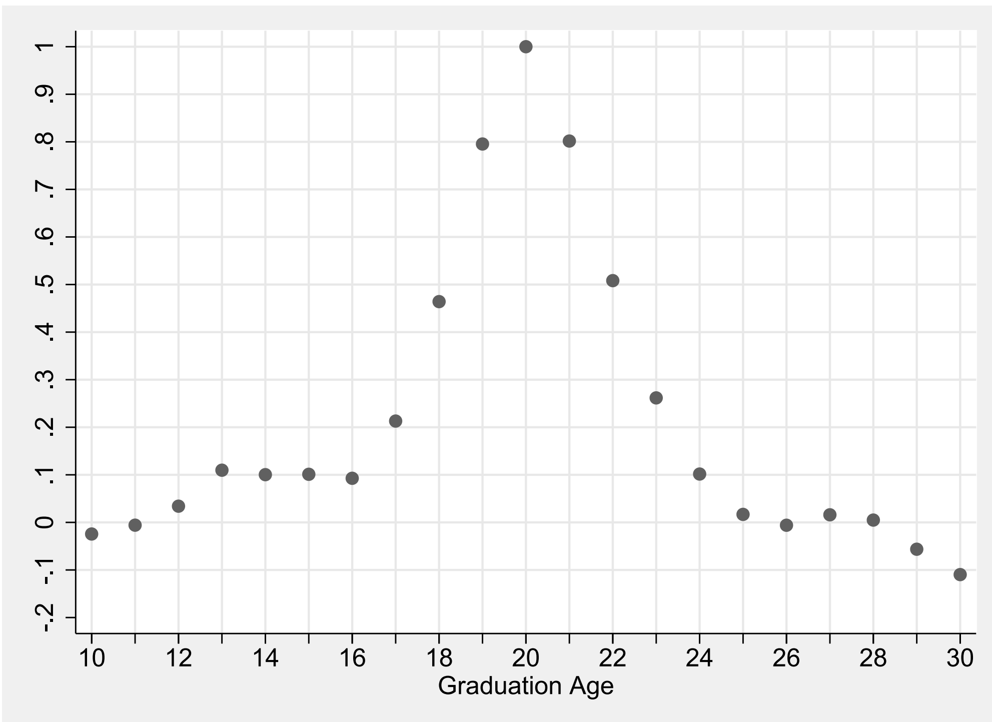
	No. Obs.	Mean	Std. Dev.
Panel A: Women			
ACS Variables			
Change in Log(Share) with 1ppt Unemp - Women	38	0.003	0.045
Share with Graduate Degree (Age 35-45)	38	0.380	0.123
Long-run average Female Share of Major	38	0.598	0.186
Share living in state of birth (Age 35-45)	38	0.526	0.070
HHI of occupations (Age 35-45)	38	0.100	0.129
Median Log(Wage) Ages 35-45 - Women	38	3.280	0.163
Share Working FTFY (35-45) - Women	38	0.571	0.052
B&B Variables			
Average GPA for Major Courses	33	3.349	0.086
Average Math GPA	28	2.621	0.233
Number of Job Interviews w/in first year	32	5.153	1.540
Median SAT Math Score/100	31	5.316	0.423
Median Number of Math Credits	34	3.854	4.100
Share Employed at 1 year	34	0.845	0.052
Share in Unrelated Jobs in first year	34	0.501	0.154
Panel B: Men			
ACS Variables			
Change in Log(Share) with 1 ppt Unemp - Men	38	0.001	0.039
Share with Graduate Degree (Age 35-45)	38	0.350	0.137
Long-run average Female Share of Major	38	0.482	0.165
Share living in state of birth (Age 35-45)	38	0.501	0.065
HHI of occupations (Age 35-45)	38	0.058	0.082
Median Log(Wage) Ages 35-45 - Men	38	3.507	0.173
Share Working FTFY (35-45) - Men	38	0.830	0.046
B&B Variables			
Average GPA for Major Courses	33	3.314	0.091
Average Math GPA	28	2.635	0.247
Number of Job Interviews w/in first year	32	5.968	1.465
Median SAT Math Score/100	31	5.491	0.456
Median Number of Math Credits	34	5.693	6.001
Share Employed at 1 year	34	0.856	0.055
Share in Unrelated Jobs in first year	34	0.474	0.150

Source: Authors' calculations from ACS and B&B data. Majors are weighted using the same weights as in Tables 1-3, 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.

A-6 Autocorrelation of National Unemployment rates.

Our discussion of Figure 8 in the main text showed that results are robust to the age at which we measure the unemployment rate. For completeness, Figure A-3 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-3: Autocorrelation of National Unemployment Rates



The figure shows the autocorrelation in unemployment rates by age for the sample used in Figure 8.

A-7 Results robust to cohort composition

As discussed in section 3.4.2 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-6 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-6: Multinomial Logit Regression with Controls for Race and Region

	(1)	(2)	(3)	(4)
Panel A: Women				
Correlation with baseline coefficients	1	0.9999	0.9999	0.9997
Coefficient on median log wage	0.1744	0.1726	0.1750	0.1734
R-squared	0.4428	0.4315	0.4443	0.4336
Panel B: Men				
Correlation with baseline coefficients	1	0.9996	0.9999	0.9997
Coefficient on median log wage	0.1366	0.1348	0.1383	0.1366
R-squared	0.3828	0.3706	0.3883	0.3760
Control for Region	N	Y	N	Y
Control for Race	N	N	Y	Y

The data used in these MNL regressions is collapsed at the gender, graduation year, major, region, race level.

A-8 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-7 and A-8 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 1960–2011 period. The second column restricts the sample to 1976–2011, 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 (+.85 for women, +.76 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. The final column presents the results from the specification that demands the most from the data. This specification replaces the major-specific quadratic trends with major-year fixed effects, which control for any unobserved changes to supply or demand for a given major that are common to individuals from all birth states. Their inclusion also changes the identification strategy to rely on only cross-sectional variation in the unemployment rate across states within a given year. The coefficients from this approach are substantively different than in the previous columns, although they are estimated without much precision. We conclude that changes to the major distribution in response to the business cycle are largely driven by the overall macroeconomic environment rather than by local deviations.

Table A-7: Log Share Regressions Controlling for National and State Unemployment Rates for Women

	(1)		(2)		(3)		(4)		(5)	
Correlation with 1976–2011 baseline beta	0.5663		1		0.8527		0.7803		-0.1253	
Coefficients on median log wage	0.1866		0.1210		0.1168		0.0590		-0.0423	
R-squared	0.4589		0.4923		0.4069		0.2757		0.2548	
Accounting	0.0729	***	0.0444	***	0.0553	***	0.0338	***	-0.0057	
Actuarial Science	-0.0446		-0.0101		0.0564		0.0636		0.1217	
Agriculture	0.1114	***	-0.0345		-0.0053		-0.0045		0.0014	
Architecture	0.0205		-0.0307	*	0.0180		-0.0067		-0.0439	
Biology Fields	0.0060		-0.0225	**	-0.0349	***	-0.0249	***	0.0002	
Business Fields, not Finance	0.0505	***	0.0211	**	0.0207	*	0.0118	*	-0.0101	
Chemistry and Pre-Med	0.0429	***	0.0019		0.0092		-0.0105		-0.0394	
Communications Fields	0.0318	***	0.0145		0.0114		0.0092		-0.0036	
Computer-Related Fields	0.1039	***	0.0938	***	0.1141	***	0.0708	***	-0.0059	
Early and Elementary Education	-0.0624	***	-0.0326	***	-0.0304	***	-0.0159	**	0.0084	
Economics	0.0651	***	0.0208		0.0307	*	0.0254	**	0.0034	
Education Fields, Other	-0.0426	***	-0.0274	***	-0.0204	**	-0.0130	**	0.0041	
Engineering Fields	0.1306	***	0.0680	***	0.0770	***	0.0469	***	-0.0098	
Environmental and Natural Resource Fields	0.0558	*	-0.0340		-0.0099		-0.0032		0.0154	
Family and Consumer Sciences	-0.0259	**	-0.0583	***	-0.0201	*	-0.0139		0.0003	
Finance	0.0688	***	0.0316		0.0698	***	0.0479	***	-0.0043	
Industrial and Commercial Arts	0.0247	*	-0.0219		-0.0089		-0.0134		-0.0266	*
Journalism	0.0323	***	-0.0117		0.0084		-0.0066		-0.0356	**
Leisure Studies	0.0212		-0.0417	***	-0.0210	*	-0.0160		-0.0057	
Liberal Arts and History Fields	-0.0269	***	-0.0157	**	-0.0068		-0.0069		-0.0050	
Literature and Languages Fields	-0.0543	***	-0.0016		-0.0109		-0.0139		-0.0117	
Mathematics and Statistics	0.0011		0.0502	***	0.0845	***	0.0489	***	-0.0170	
Natural Science Fields, Other	0.0430	***	0.0246	**	0.0242	*	0.0074		-0.0206	
Nursing	0.0440	***	0.0021		-0.0074		-0.0049		0.0002	
Other Fields	0.0277		-0.0149		0.0382		0.0135		-0.0265	
Pharmacy	0.0788	***	0.0517	**	0.0377		0.0127		-0.0190	
Physics	0.0153		0.0418	*	0.0657	**	0.0323		-0.0126	
Political Science and International Relations	0.0170	*	0.0251	***	0.0253	**	0.0030		-0.0308	*
Pre-Law and Legal Studies	0.0474	**	0.0613	**	0.0584	**	0.0412	**	0.0097	
Protective Services	0.0479	***	-0.0077		0.0021		-0.0010		-0.0028	
Psychology Fields	-0.0274	***	-0.0090		-0.0132		-0.0164	**	-0.0127	
Public Affairs, Health, Policy	0.0172	*	0.0028		0.0324	*	0.0168		-0.0147	
Social Science Fields, Other	-0.0387	***	-0.0196		-0.0122		-0.0179		-0.0175	
Social Work	-0.0103		-0.0261	*	-0.0167		-0.0069		0.0111	
Sociology	-0.0769	***	-0.0371	**	-0.0328		-0.0249	**	-0.0003	
Technical Engineering Fields	0.0622	**	-0.0058		0.0481	*	0.0266	*	-0.0016	
Technical Health Fields	0.0371	***	0.0040		0.0041		-0.0038		-0.0107	
Visual and Performing Arts	-0.0078		-0.0349	***	-0.0313	**	-0.0147	**	0.0153	

Note: Column (1) represents the baseline national coefficients using the 1960-2011 sample. Column (2) represents the baseline national coefficients using the 1976-2011 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. Column (5) uses state-level unemployment rates and major $\times$ year dummies.

Table A-8: Log Share Regressions Controlling for National and State Unemployment Rates for Men

	(1)	(2)	(3)	(4)	(5)
Correlation with 1976–2011 baseline beta	0.8156	1	0.7642	0.7973	0.0068
Coefficients on median log wage	0.1378	0.1026	0.0775	0.0524	-0.0055
R-squared	0.3792	0.4861	0.2150	0.2652	0.0030
Accounting	0.0593 ***	0.0337 **	0.0453 ***	0.0283 **	-0.0023
Actuarial Science	0.0372	0.0969	0.1438 ***	0.0932 ***	-0.0319
Agriculture	0.0235 **	-0.0017	0.0273	0.0087	-0.0129
Architecture	-0.0167 *	-0.0284 ***	0.0084	0.0016	-0.0112
Biology Fields	-0.0051	-0.0090	-0.0012	-0.0135	-0.0202
Business Fields, not Finance	0.0007	-0.0148	-0.0184	-0.0097 *	-0.0013
Chemistry and Pre-Med	0.0382 ***	0.0142 *	0.0305 **	0.0142	-0.0073
Communications Fields	0.0129 **	-0.0006	-0.0052	-0.0099	-0.0199
Computer-Related Fields	0.0339 **	0.0164	0.0407 *	0.0203	-0.0183
Early and Elementary Education	-0.1254 ***	-0.0909 ***	-0.0066	-0.0228	-0.0230
Economics	0.0175 **	0.0198 *	0.0161	0.0035	-0.0231
Education Fields, Other	-0.0607 ***	-0.0404 ***	-0.0261 **	-0.0123	0.0144
Engineering Fields	0.0524 ***	0.0275 ***	0.0229 **	0.0147 **	-0.0041
Environmental and Natural Resource Fields	0.0113	-0.0028	0.0189	0.0012	-0.0059
Family and Consumer Sciences	-0.0201	0.0071	0.0999 ***	0.0435 **	-0.0504
Finance	0.0199	0.0033	0.0166	0.0042	-0.0257 *
Industrial and Commercial Arts	-0.0253	-0.0325 *	-0.0238	-0.0170	-0.0045
Journalism	0.0188	-0.0080	0.0296 *	0.0174	-0.0088
Leisure Studies	-0.0458 **	-0.0343	0.0206	0.0043	-0.0036
Liberal Arts and History Fields	-0.0427 ***	-0.0202 **	-0.0002	-0.0056	-0.0083
Literature and Languages Fields	-0.0554 ***	-0.0037	0.0175	-0.0030	-0.0306 *
Mathematics and Statistics	-0.0033	0.0271 ***	0.0621 ***	0.0371 ***	-0.0088
Natural Science Fields, Other	0.0690 ***	0.0469 ***	0.0751 ***	0.0228 **	-0.0476 ***
Nursing	0.0405 **	0.0172	0.0557 ***	0.0390 **	0.0202
Other Fields	0.0032	-0.0159	0.0034	0.0074	0.0099
Pharmacy	0.0663 ***	0.0564 **	0.0577 **	0.0373 *	0.0193
Physics	0.0180	0.0226	0.0634 **	0.0256	-0.0385 **
Political Science and International Relations	-0.0060	0.0199 *	0.0147	0.0047	-0.0114
Pre-Law and Legal Studies	0.0308	0.0478	0.0508 *	0.0285	0.0081
Protective Services	0.0153	0.0148	0.0290 *	0.0207 *	0.0148
Psychology Fields	-0.0354 **	-0.0018	0.0004	0.0139	0.0386 ***
Public Affairs, Health, Policy	0.0200	0.0116	0.0744 **	0.0561 ***	0.0338
Social Science Fields, Other	-0.0480 ***	-0.0206	0.0136	0.0019	-0.0084
Social Work	0.0119	0.0340	0.0347	0.0279	0.0398 *
Sociology	-0.1082 ***	-0.0518 **	0.0014	0.0002	0.0128
Technical Engineering Fields	0.0036	-0.0086	0.0405 **	0.0120	-0.0323 ***
Technical Health Fields	0.0221	0.0353 *	0.0587 ***	0.0354 **	0.0052
Visual and Performing Arts	-0.0175 *	-0.0355 ***	-0.0172	-0.0259 ***	-0.0326 **

Note: Column (1) represents the baseline national coefficients using the 1960-2011 sample. Column (2) represents the baseline national coefficients using the 1976-2011 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. Column (5) uses state-level unemployment rates and major $\times$ year dummies.

A-9 No evidence that marginal individuals end up in tails of wage distribution

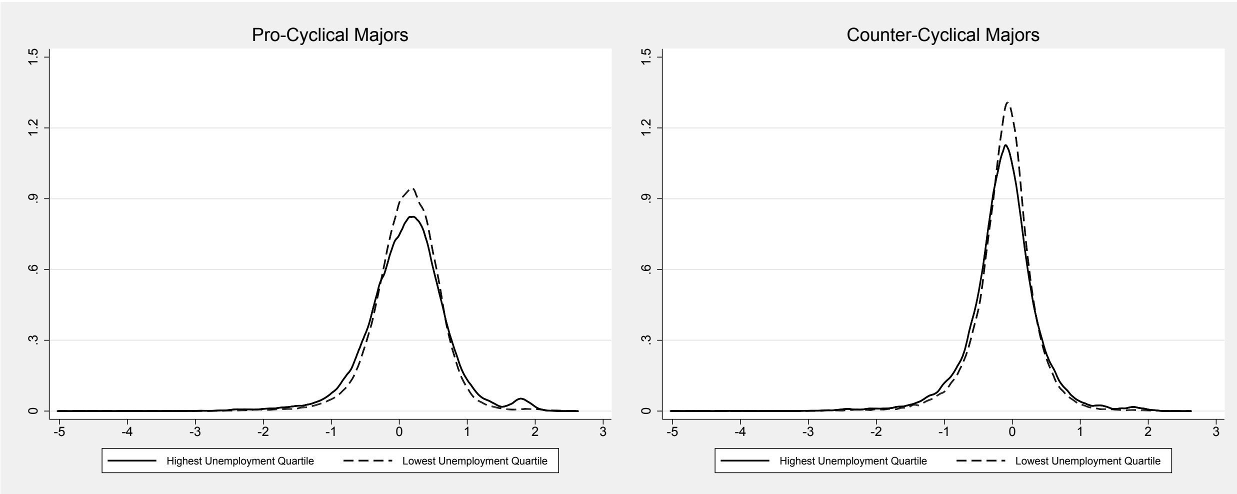
As discussed in the main text, we considered the possibility that individuals choosing a different major as a result of the business cycle may have less of a comparative advantage in their eventual major than in their counterfactual major. For example, the marginal business or engineering student may 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.

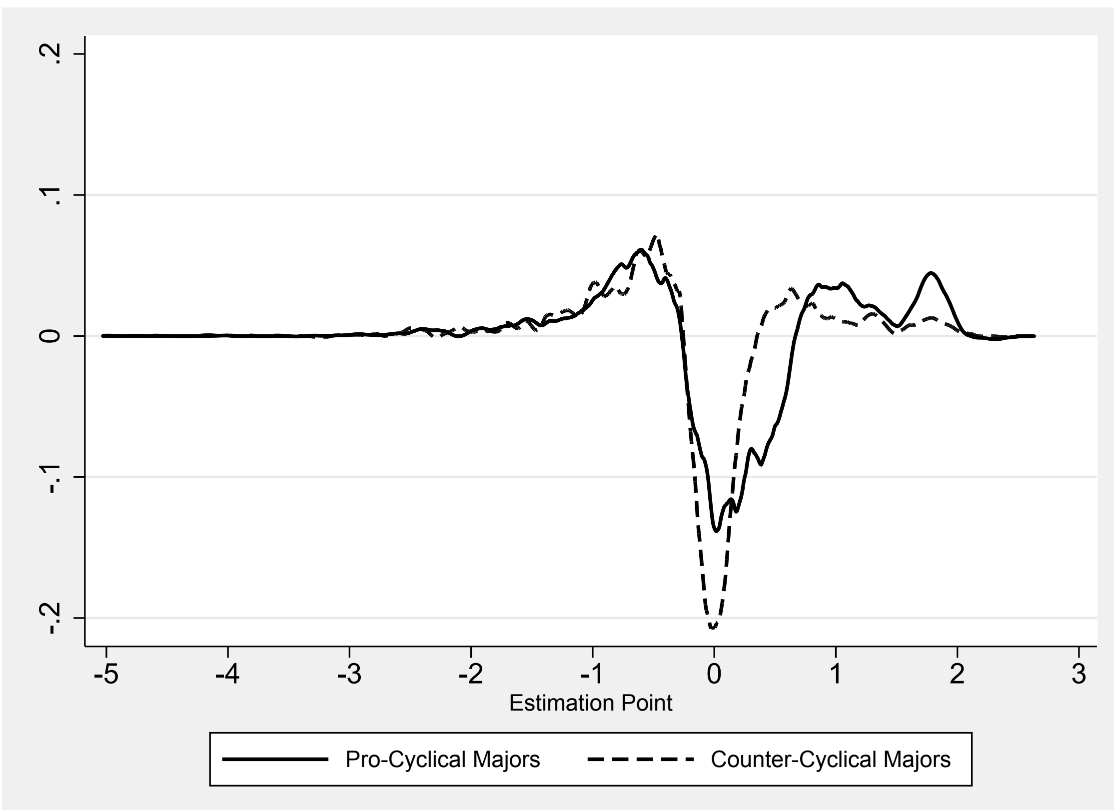
Figures A-4 and A-5 provide the results of this exercise for women and for men respectively. For both types of majors, there is a leftward shift in the middle of the distribution when comparing high unemployment rate cohorts to low unemployment rate cohorts. This shift is consistent with the literature 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-4: Log Wage Residuals for Women

(a) Distribution of Wage Residuals by Unemployment Rate



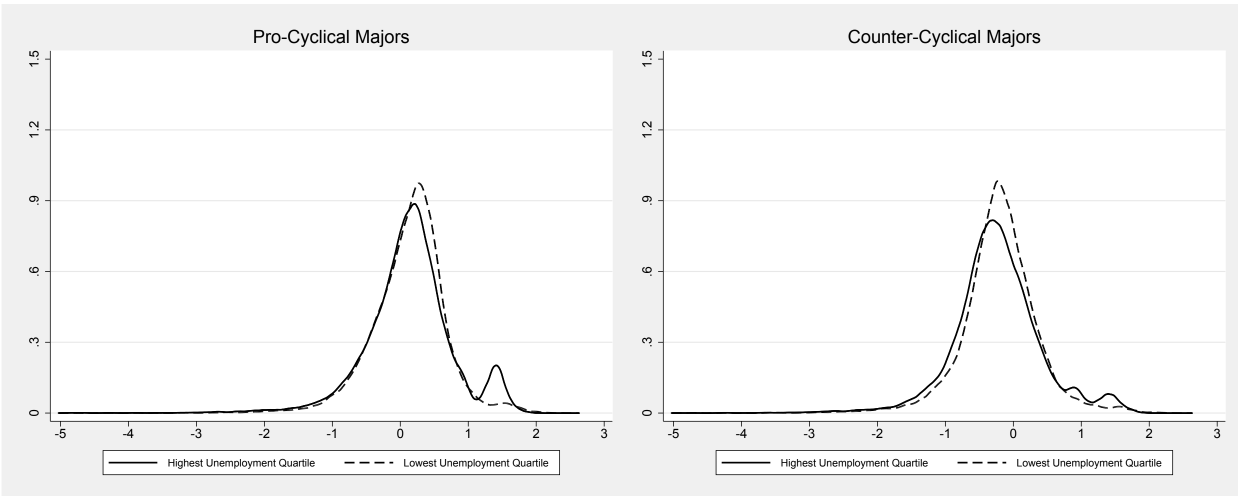
(b) Difference in Wage Residual Densities (Highest-Lowest Unemployment Rate Quartile)



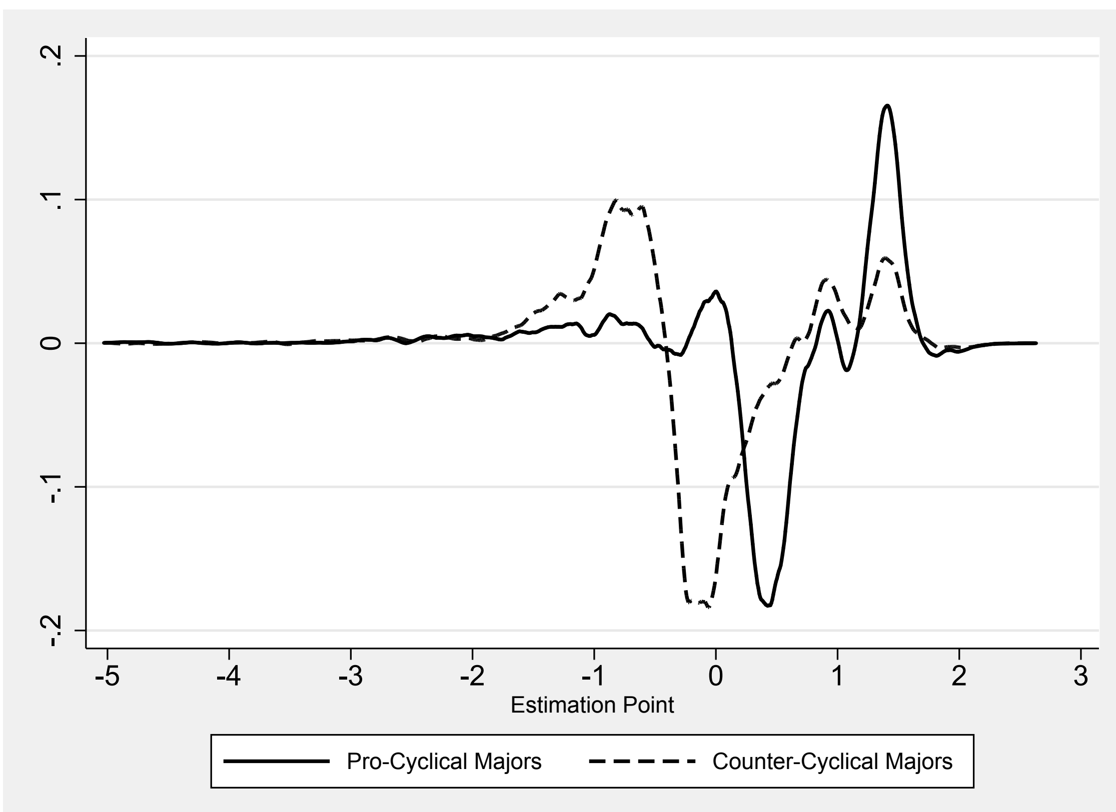
Note: Note: The lines in the bottom panel represent the difference in estimated densities for each of the graphs in the top panel.

Figure A-5: 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.