College Major Choice Over the Business Cycle*

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Abstract

This paper explores the relationship between the business cycle and college major choices among bachelor 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 lead more often to professional work in a related field. Notably, women are more responsive than men are, and recessions prompt more women to enter male-dominated fields. Recessions also encourage students to pursue more difficult majors, such as STEM fields, which implies scope for encouraging additional STEM majors during stronger labor markets even with prevailing levels of academic preparation among college students. 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.
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1 Introduction

Investment in human capital through education is one of the primary drivers of the growth of the modern economy. As a result, an extensive literature has explored the ways in which students approach the human capital investment decision and the resulting investment outcomes. Primarily, this literature has focused on the "extensive margin" of the investment decision: whether to enroll and complete additional years of post-secondary schooling.[1] This choice is a crucial one to make, as the wage gap between college and high school graduates is large (Grogger and Eide 1995), 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 college investment decision including credit constraints (Carneiro and Heckman 2002, Lochner and Monge-Naranjo 2011), 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 forthcoming). The benefits of college enrollment and completion are generally large and well-established (Carneiro, Heckman and Vytlacil 2011).

However, recent work has suggested that the intensive margin of choice of college major 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 focused on a static "point-in-time" framework or based the analysis on a single cohort, largely due to data limitations.

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? Previous studies have found a substantial influence of the business cycle on other facets of human capital investment

[1] 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.

[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 (forthcoming), and Zafar (2011).

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).[3] Additional research has investigated the role of economic conditions on the choice of specific careers, such as engineering (Freeman 1975) 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 intensive 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) of a major. We consider 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.

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, this new data from the ACS allows us to trace out the 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 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 time-series evidence that the share of college majors is starkly responsive

[3]See also Dellas and Sakellaris (2003) and Barr and Turner (2013) on enrollment, and Light and Strayer (2000) and Bound, Lovenheim and Turner (2009) on college completion.

to the business cycle. The dotted line in the figure shows the time-series from 1960 to 2010 of expected earnings for men with a Bachelor's degree who turned 20 during the reference year.[4] 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.[5] 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 = +0.59).

This striking figure motivates our subsequent empirical analysis. Using de-trended multinomial logit regressions (or linear approximations thereof), we estimate the responsiveness of choices among 38 college major categories 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. Adding up the average marginal effects from a multinomial logit reveals that a one percentage point increase in the unemployment rate leads to a 2.7 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.

Based on the coefficient estimates from these regressions, we investigate which majors are most affected by the business cycle. For men, the most 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. This set of findings reveals that in the face of a tight labor market, students choose more applied fields with more relevant job training, rather than fields with broader content.

This quantification of how each major's popularity responds to changes in the unemployment rate prompts our second research question: What (permanent) characteristics of

[4]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.

[5]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. Thus, the responses we find are likely underestimates of the true amount of cyclical responses.

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 explains 34 to 43 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 1.3 percentage point more positive share elasticity in response to the unemployment rate, a result that is consistent across men and women.

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. A potential explanation is that students facing weak labor markets prefer to have 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 a recession likely understate the independent 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 0.6 log points of expected earnings for "recession" conditions of an unemployment rate three percentage points above average.[6] Notably, the average observed wage declines due to the business cycle, therefore, represent a weighted average of earnings *increases* for a minority of students and large earnings declines among the remainder.

This set of findings thus demonstrates an additional margin upon which students adjust in response to labor market conditions. These results also have important implications across a range of literatures beyond this specific question. In particular, we show that women are especially responsive to changes in economic conditions in their choice of college majors. This finding 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 2013). 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 1975, Oyer 2008, Goldin and Katz 2012) 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

[6] As we discuss in more depth in the relevant section, 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, von Wachter and Heisz 2012, Altonji, Kahn and Speer 2013).

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 significant the bias from ignoring the reallocation of college majors during recessions is when estimating the costs of graduating in a recession; 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. Given our data limitations, 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.[7]

We begin by defining the utility of major m for student i in cohort c to be U_{icm}. In a life-cycle context, as in Altonji (1993), Arcidiacono (2004), and Altonji 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.[8]

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

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

The fixed component of the utility "return" to a major, η_m captures all of the fixed (across cohorts) components of the major's potential employment and wage opportunities, as well as non-pecuniary costs and benefits, over the life-cycle. For example, a degree in Engineering

[7]Previous research has often used assumptions regarding rational expectations (see, e.g. Berger (1988)), or myopic expectations (as in Freeman (1975)) 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.

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

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 1960-2010), 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 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 major-specific quadratic 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 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 $\beta_m * unemp_c$. The only restriction here is one of linearity, i.e. that the major-specific effect of the unemployment rate (at age 20) on the utility of each major is linear with respect to the unemployment rate.

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 $U_{icm^*} > U_{icm}\ \forall m \neq m^*$. Note that because the unemployment rate is a $c \times m$ characteristic, we should not run conditional logit models without correcting for the correlation in the error terms. In fact, in our main specifications we instead 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 major 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 without loss of generality, we can call it $e^{-\gamma_c}$.

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

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 $f_m(c) = \delta_m^1 c + \delta_m^2 c^2$, 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 address the fact that the variance of the resulting error term depends in part on π by using heteroskedasticity-robust standard errors. Further, we note that we rely on cohort-level variation in unemployment rates for identification, so we need a relatively long time dimension of the panel, and we cluster our standard errors at the cohort level, the effective level of variation.

A semi-elasticity regression specification such as this one faces the challenge that we cannot separately identify 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 scaled 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 does 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 that 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.[9] All respondents in this roughly one percent cross-sectional sample of the U.S. 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 four annual surveys from 2009-2012, we are thus able to calculate the distribution of college majors for cohorts turning age 20 from 1960-2010 based on a roughly four 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.[10] 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 the 1993 wave of the Baccalaureate and Beyond survey

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

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

(B&B).[11] 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.[12]

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 (j) $\times$ birth cohort (c) cells as observations, which is motivated by the discussion in the previous section.[13] We use the 38 major classifications discussed previously and the 51 birth cohorts that turned 20 years old in the years 1960-2010. All of the analysis is run separately for men and women.

$$y_{jc} = \alpha_j + \beta_j * \text{unemp_20}_c + \gamma_j^1 * \text{trend}_c + \gamma_j^2 * \text{trend}_c^2 + \epsilon_{jc} \tag{7}$$

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, controlling for major-specific quadratic trends.[14] Because the unemployment rate varies only by birth cohort, we calculate standard errors that are clustered at that level.

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. Figure 2, which

[11] 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.

[12] Two categories, Actuarial Science and Pharmacy, are not represented in the B&B data and therefore are not included in the analysis in Section 3.3.

[13] 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.

[14] For a detailed examination of the determinants of these long-run trends, see Gemici and Wiswall (2014).

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 1960-2010. 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.[15] 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 pro-cyclical while the share choosing Early and Elementary Education is strongly countercyclical. The estimated coefficients are +0.12 for Engineering and -0.065 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 twelve 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 similar coefficient estimates of the cyclicality of each of the 38 major categories. In general, the results are as expected given 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: 23 of the 38 majors have an unemployment gradient that is statistically significant at the 0.01 level, and an additional six 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 percentage 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

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

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.[16] The semi-elasticity results for men are given in Figure 5 and share estimates are in Figure 6. Appendix Table A-2 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 field in response to fluctuations in the unemployment rate. Adding up the absolute value of the coefficients for shares yields over four percentage points in total reallocation among women as opposed to 2.5 percentage points among men. The stronger response among women along this margin is consistent with women having more elastic labor supply generally (Killingsworth and Heckman 1986, Heckman 1993, Blau and Kahn 2007). 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 attributes of college majors that are associated with the 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. 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.[17] 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

[16] 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-3 shows the difference in coefficients, including tests of the differences in elasticities between genders.

[17] Summary statistics for each of these variables is available in Appendix Table A-4.

characteristics as explanatory variables. 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 changes in a major's market share due to higher unemployment, conditional on fixed characteristics and 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. (2013), 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 pursue this information during a time of labor market distress. This type of more intensive 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 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 majors with ten percent greater long-run median wages experience a 1.3 percentage point larger gain in share due to a one percentage point increase in the unemployment rate. Each of the additional entries in Table 1 provides the corresponding coefficient from a similar bivariate regression with the same dependent variable (cyclical percentage changes in share) 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 make *permanent* investments in fields of study with more favorable long-run labor market potential when the macroeconomy is relatively weak.

The next sets of 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 majors. Recall that these are intended to be "typical" short-run characteristics of the majors, calculated from a single cross-section, and thus 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 females (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.[18] 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-typical major (Turner and Bowen 1999, Goldin 2013).

Additionally, the fact that women are more likely to choose these majors in a reces-

[18]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.

sion provides some insight into what types of policy interventions may prove effective in encouraging women to pursue male-dominated fields. 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 2014).

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 no support for the hypothesis that students differentially select majors that are more spatially mobile. Despite the fact that college completion has been shown to causally increase geographic mobility (Malamud and Wozniak 2012), perhaps surprisingly this mobility does not differentially increase during recessions. We also find no evidence that 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). Thus, although we find that students are selecting majors that typically experience smaller adverse income shocks due to recessions, we find no evidence that they move toward majors that provide greater career flexibility.

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 statistically significantly different from zero only for women. 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 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 life-cycle model of college major choice (as in Berger (1988)), students' major decisions should respond exclusively to long-run earnings prospects, assuming fully forward looking agents with exponentially discounted time preferences. 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 earnings and employment probabilities of a graduate's major.

Tables 2 and 3 present the multivariate results for women and men, 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 more than a third of the variation 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.

In the remaining columns, we add an additional covariate to examine whether any of the previously discussed correlations remain after controlling for these changes in relative labor market returns. Column 4 reveals that, even conditional on changes in earnings, recessions induce women to choose gender-atypical fields. Perhaps relatedly, column 5 reveals that women choose more difficult majors during recessions, even controlling for the fact that more difficult majors typically experience smaller declines in expected earnings. Finally, column 6 shows that women are also 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.

For men, long-run earnings and the ease of finding a (related) job are similarly strong

predictors. Male college students appear to respond to economic downturns by moving into fields with higher long-run earnings prospects, as this explains over 42% of the variation in major cyclicality. Although there is some weak evidence of men moving into male-dominated and more difficult fields, there is no significant evidence of men choosing more career oriented majors. These findings support the view that long-run earnings prospects alone are not a sufficient statistic for understanding the responsiveness of 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.

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 analyses of the earnings losses of graduating in a recession incorporate the impact of this compensating behavior. In this subsection, we discuss one approach to estimating the magnitude of the omitted variable bias from failing to consider the major-reallocation response to recessions. 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 ($majorval$):

$$log(earnings)_c = \beta_0 + \beta_1 unempgrad_c + \beta_2 majorval_c + \epsilon_c \tag{8}$$

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 causal effect of the unemployment rate on $log(earnings)$.[19] 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:

$$log(earnings)_c = \tilde{\beta}_0 + \tilde{\beta}_1 unempgrad_c + \tilde{\epsilon_c} \tag{9}$$

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

with the standard omitted variable bias to β_1:

$$\tilde{\beta_1} = \beta_1 + \beta_2 \frac{Cov(majorval, unempgrad)}{Var(unempgrad)} \tag{10}$$

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

$$majorval_c = \gamma_0 + \gamma_1 unempmid_c + \eta_c \tag{11}$$

Again, relying on the assumption that the unemployment rate at graduation is unrelated to the residual in the major value equation, the omitted variable bias expression in (10) simplifies to:

$$\tilde{\beta_1} = \beta_1 + \beta_2 \gamma_1 \delta_1 \tag{12}$$

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

Therefore, the coefficient on the unemployment rate at graduation will be biased when omitting the composition of majors as long as the product $\beta_2 \gamma_1 \delta_1$ is not zero. The numerical value of the bias 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 $+0.45$.[20] Thus, the total omitted variable bias 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.

[20]This specification is run using data from 1960-2012, and it includes the same quadratic trends used in the main analysis.

4.1 Quantifying the Bias

Quantifying the magnitude of this bias requires numerical estimates of the first and second regression coefficients in addition to the +0.45 estimate of δ_1. Doing so requires a more exact definition of *majorval*. In the analysis that follows, we calculate *majorval* as the weighted average of the median mid-career (ages 35-45) log(earnings) associated with a major. Importantly, we treat this characteristic of majors as constant across cohorts, but the weights on each major, π_{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

$$\bar{x_1} - \bar{x_0} = \sum_j (\pi_{j1} - \pi_{j0}) x_j. \tag{13}$$

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 $\pi_{j1} - \pi_{j0} = \left(e^{\beta_j^{unemp}} - 1\right) \cdot \pi_j^0$, and then multiply each difference in major share by that major's long-run earnings, $\bar{x}$.[21]

Taking the weighted sum of the changes in shares across all 38 majors yields approximately +0.45 log points. In other words, the increase in *permanent* earnings capacity of a cohort rises by roughly 0.45 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.[22] To obtain the effect of an increase in unemployment at the time of graduation, we scale this coefficient by 0.45, 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

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

[22] The weighted change in log(median earnings) with each one percentage point increase in the unemployment rate is 0.43 for men and 0.48 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.

to have major-based earnings capacity that is $0.45 * 0.45 * 3 \approx 0.6$ log points higher than the cohort graduating with average unemployment.[23]

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 omitted 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 bias calculation, given that recessions tend to expand the earnings gaps between high-paying and low-paying majors (Oreopoulos et al. 2012, Altonji et al. 2013).

These calculations thus imply that an analysis that treats the major distribution as fixed will have a positive bias of roughly 0.6 log points. Compared to typical estimates in the -6 to -8 log point range, e.g. (Kahn 2010), this bias is not insignificant, but it does imply that labor demand conditions have an even stronger adverse effect on young graduates than previously estimated. Our results imply 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 1.35 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. 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 1.35 percent of earnings *on average* reflects substantial heterogeneity between marginal and inframarginal individuals. Among those who switch 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.

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,

[23]This characterization of a "recession" is the same as used in Altonji et al. (2013).

the average gains among switchers would be larger than the resulting demand shock.[24] Thus, many students who face high unemployment during and immediately after college actually experience an *increase* in lifetime earnings because the recession changes their investment in human capital through the intensive margin of major choice.

5 Conclusion

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. Using data on college major choice from the American Community Survey for cohorts graduating between 1962 and 2012, 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 2.7 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

[24] 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.

complete more challenging majors, such as STEM fields, yet choose not to do so in periods with stronger labor market prospects. 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 greater take-up of these more difficult fields even in a healthy labor market.

Finally, we use our findings to estimate the bias from estimating the impact of graduating in a recession without accounting for the endogenous changes in the distribution of college majors. Relative to the estimated impact of graduating in a recession on the order of 6 percent, we find that this coefficient is biased downwards by roughly ten percent. In other words, the offsetting labor supply response along this intensive margin is one-tenth of the demand effect of graduating in a recession, and thus 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 subtle ways to temporary disruptions in labor demand.

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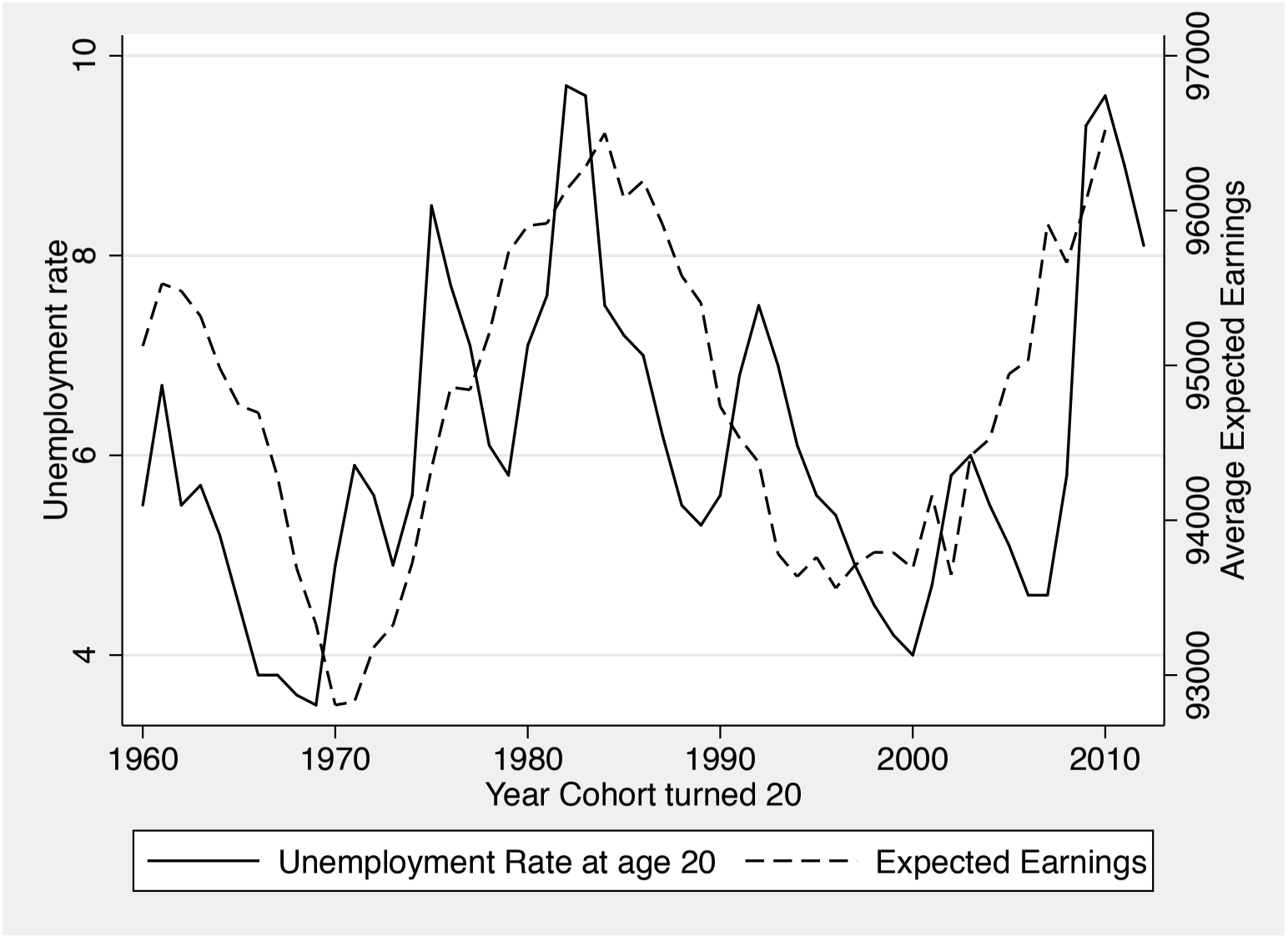
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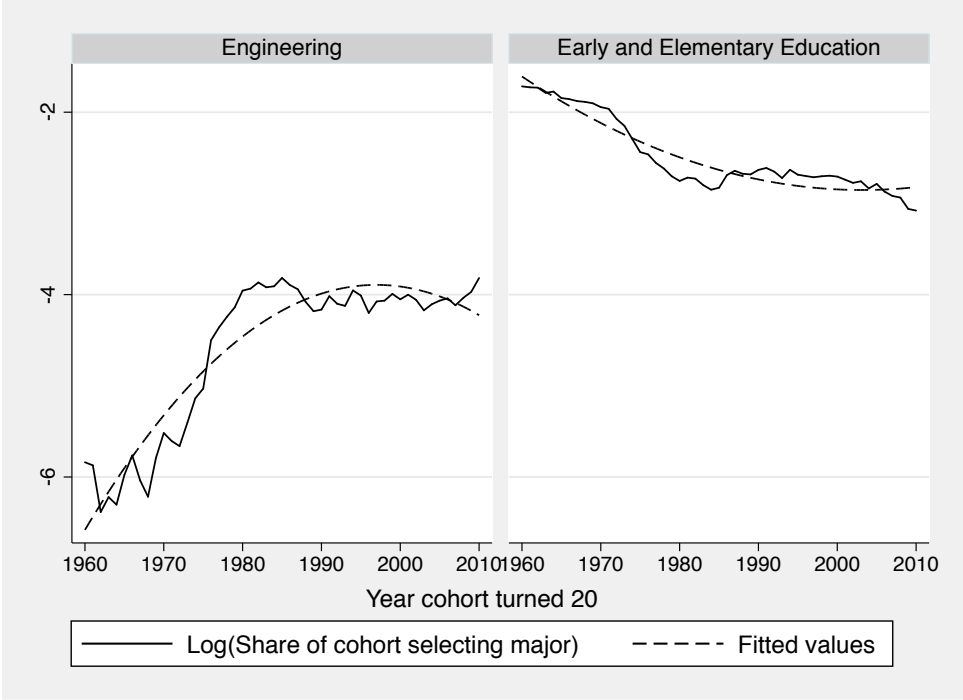
Figure 1: Business Cycles and Average Major-Based Earnings



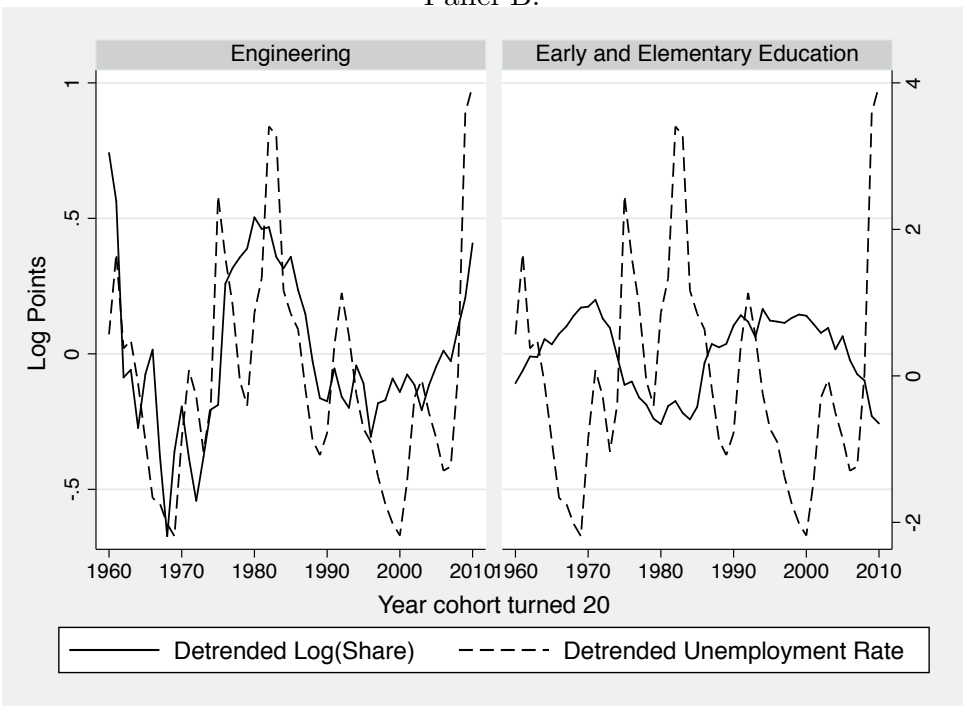
Source: Bureau of Labor Statistics (unemployment rate) and authors' calculations from IPUMS 2009-2012 (average expected earnings). Average expected earnings for a field of study are based on 2009-2012 earnings data among men ages 35-45 who are employed full time (at least 35 hours per week), full year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

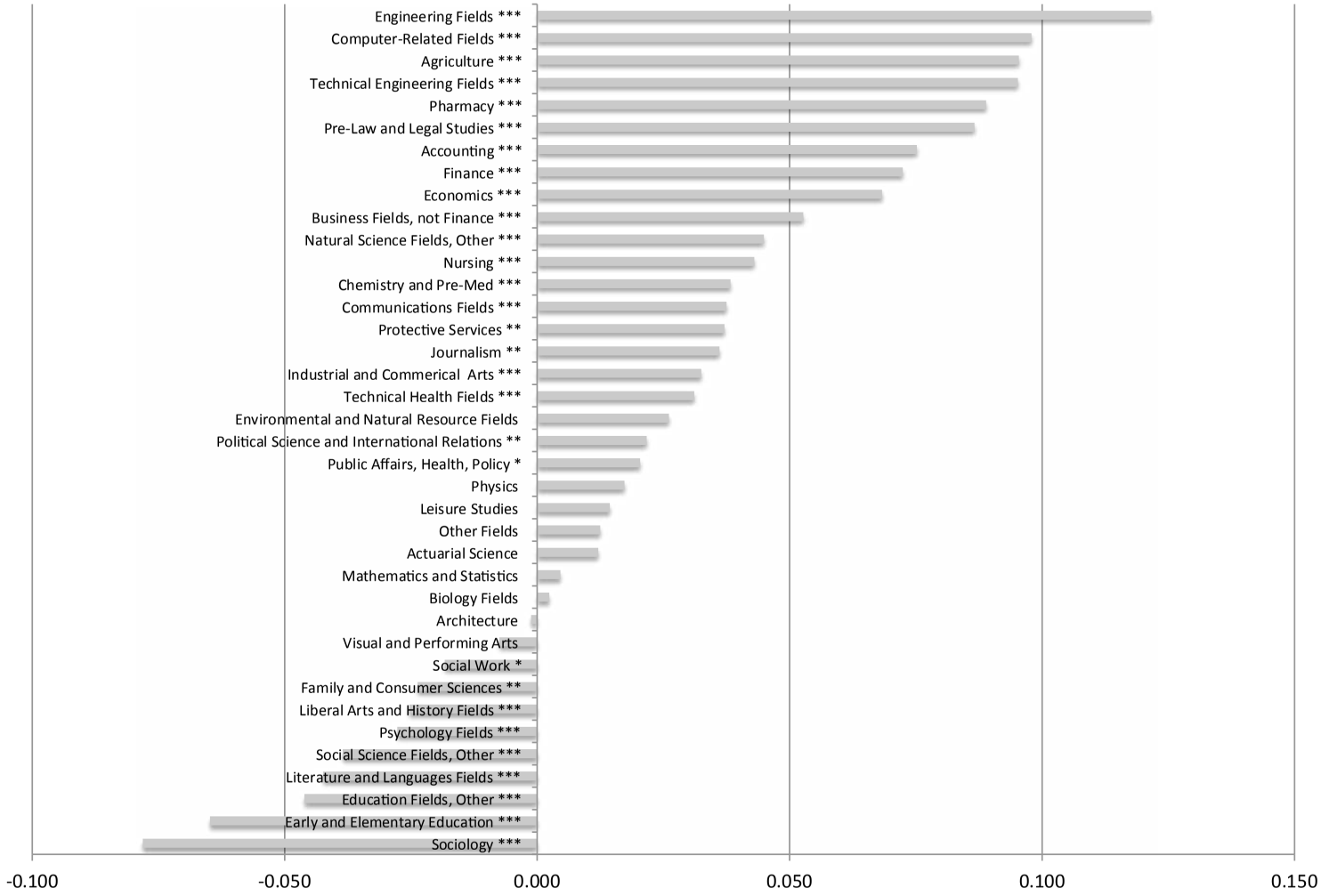


Panel B:



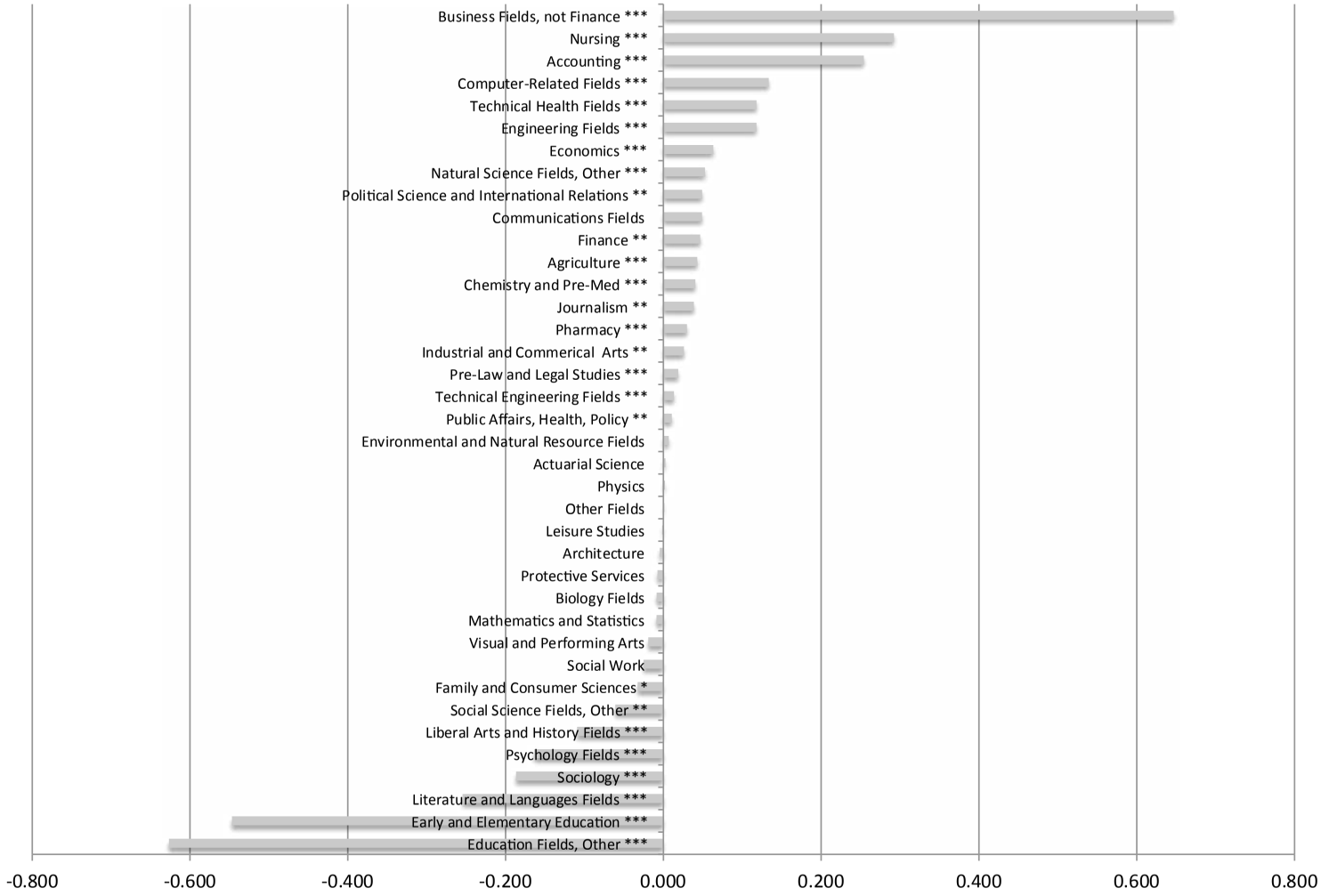
Data sources: BLS and authors' calculations from 2009-2012 ACS data. This analysis is based on the fields of study for birth cohorts of women who completed college degrees. Panel A shows the raw data and best fit quadratic trends for the log(share) of graduates completing degrees in Engineering and Early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



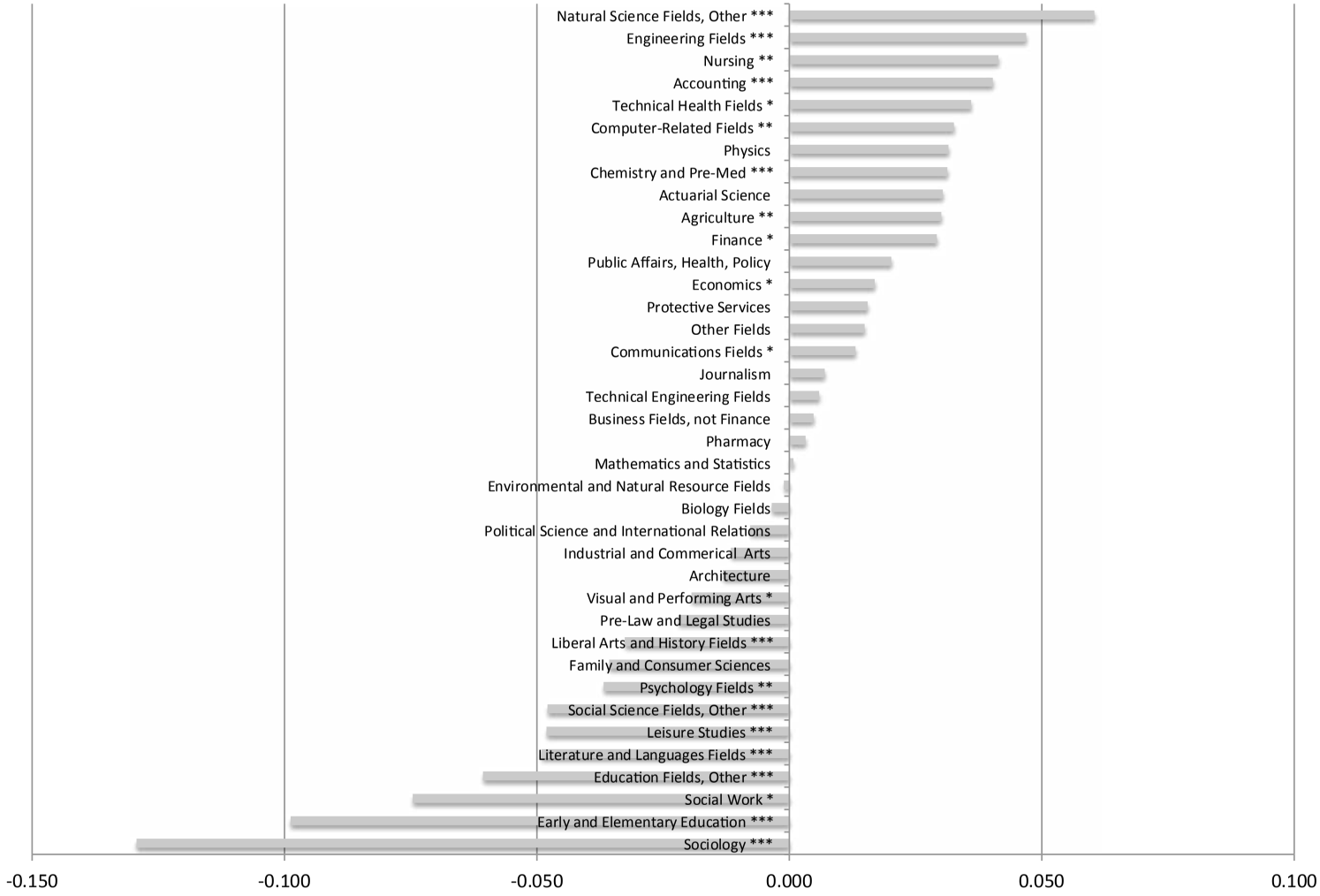
Data sources: BLS and authors' calculations from 2009-2012 ACS data. These coefficients represent the change in log(share) of a birth cohort selecting a given major category due to a one percentage point increase in the unemployment rate and are based on Equation 7, which includes major fixed effects 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-2 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



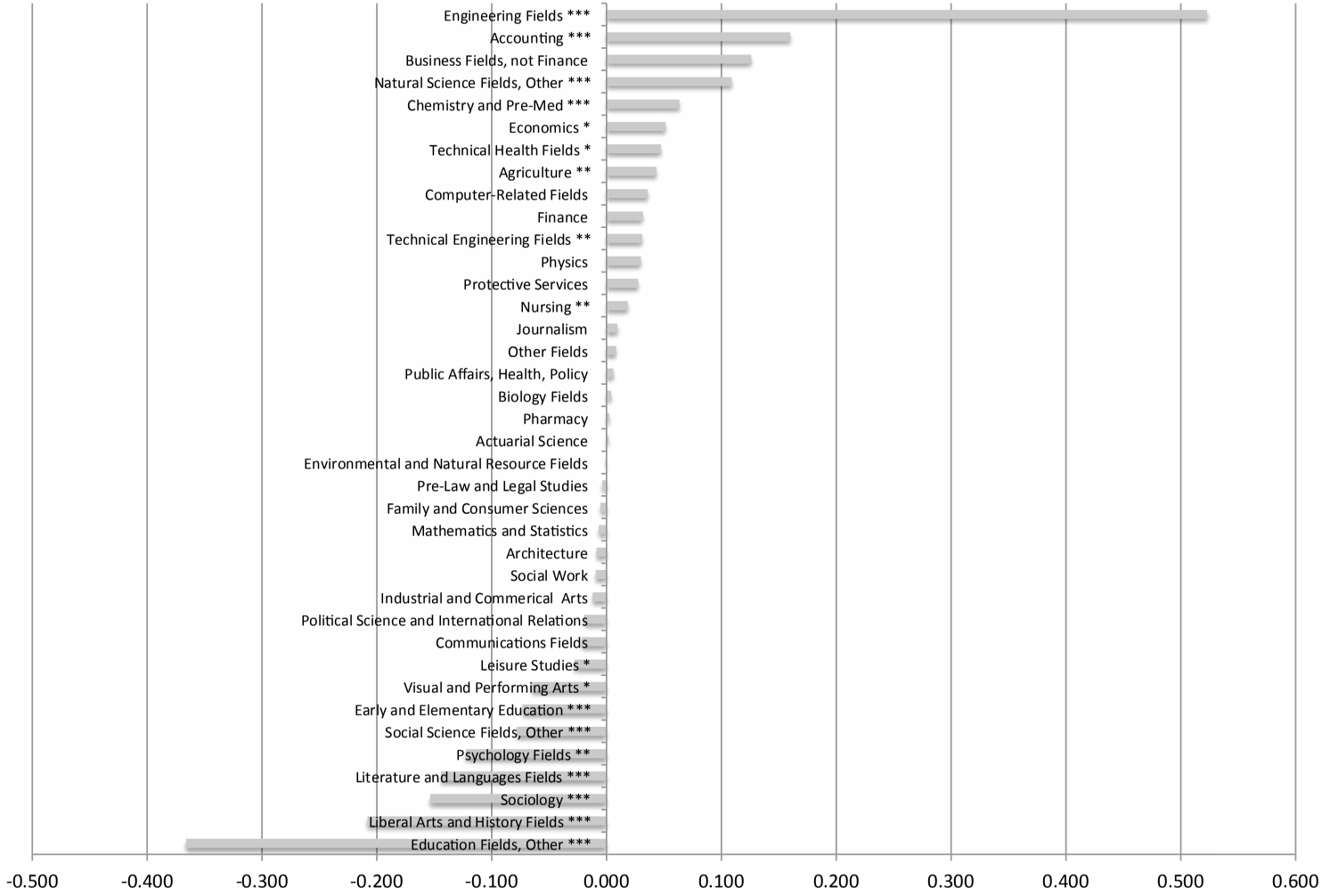
Data sources: BLS and authors' calculations from 2009-2012 ACS data. These coefficients represent the change in share of a birth cohort selecting a given major category due to a one percentage point increase in the unemployment rate and are based on Equation 7, which includes major fixed effects and 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-2 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



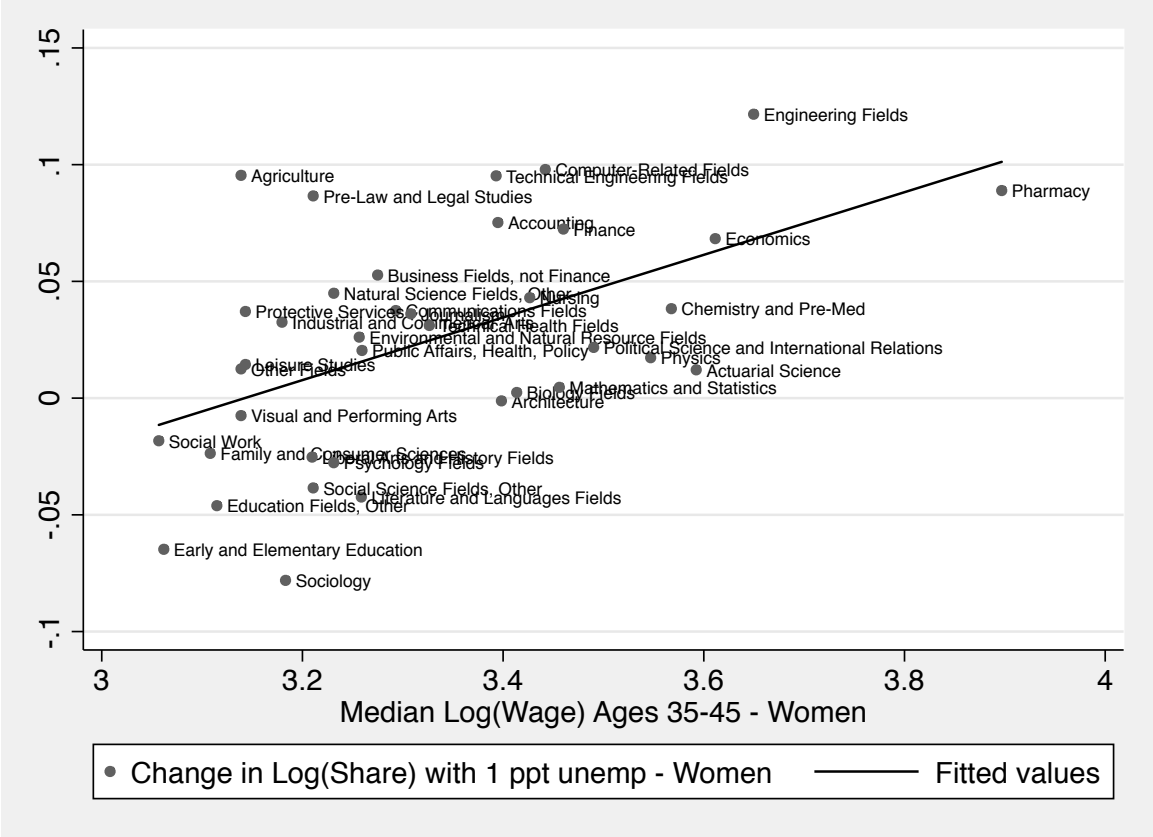
Data sources: BLS and authors' calculations from 2009-2012 ACS data. These coefficients represent the change in log(share) of a birth cohort selecting a given major category due to a one percentage point increase in the unemployment rate and are based on Equation 7, which includes major fixed effects 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-2 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-2 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 fitted line represents the predicted values from an OLS regression. The dependent variable is the major-specific coefficient on the unemployment rate from the analysis in Figure 3. Long-Run Earnings are the median log(earnings) of women ages 35-45 working full-time, full-year in 2009-2012.

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	0.134***	(0.0324)	0.125***	(0.0322)
Share Working FTFY (35-45)	0.435***	(0.110)	0.565***	(0.143)
Labor Market Prospects - Short Run				
Number of Job Interviews w/in first year	0.0186***	(0.00503)	0.0105**	(0.00509)
Share Employed at 1 year	0.202*	(0.0992)	0.187*	(0.104)
Share in Unrelated Jobs in first year	-0.159***	(0.0498)	-0.136***	(0.0382)
Difficulty				
Median SAT Math Score/100	0.0440**	(0.0167)	0.0464***	(0.0142)
Average Math GPA	0.0653*	(0.0371)	0.0780**	(0.0356)
Average GPA for Major Courses	-0.305***	(0.0674)	-0.164**	(0.0690)
Other				
Long-run average Female Share of Major	-0.118***	(0.0348)	-0.0997***	(0.0336)
Share living in state of birth (Age 35-45)	0.0273	(0.131)	-0.138	(0.106)
HHI of occupations (Age 35-45)	-0.00419	(0.107)	-0.0531	(0.0840)
Share with a grad degree (Age 35-45)	-0.121**	(0.0452)	-0.0476	(0.0440)

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-4 provides summary statistics, including means, standard deviations and the number of valid observations for each of these characteristics.

Table 2: Correlates of Cyclical Changes in Major Shares Among Women - Multivariate Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Median Log(Wage) Ages 35-45 - Women	0.180***	0.121**	0.0713*	0.0332	0.0645**	0.0481
	(0.0415)	(0.0470)	(0.0389)	(0.0322)	(0.0272)	(0.0327)
Number of Job Interviews w/in first year		0.0129**	0.0166***	0.0124***	0.0110***	0.0158***
		(0.00472)	(0.00291)	(0.00364)	(0.00265)	(0.00279)
Share in Unrelated Jobs in first year			-0.160***	-0.167***	-0.153***	-0.142***
			(0.0354)	(0.0366)	(0.0291)	(0.0306)
Long-run average Female Share of Major				-0.0862***		
				(0.0306)		
Average GPA for Major Courses					-0.185***	
					(0.0523)	
Share Working FTFY (35-45) - Women						0.259***
						(0.0779)
Constant	-0.572***	-0.450***	-0.231*	-0.0346	0.432**	-0.309**
	(0.138)	(0.140)	(0.123)	(0.105)	(0.182)	(0.113)
Observations	32	32	32	32	32	32
R-squared	0.344	0.481	0.689	0.777	0.767	0.763

Robust standard errors in parentheses. *** p¡0.01, ** p¡0.05, * p¡0.1. 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) calculated among women as the dependent variable. These coefficient estimates are available in Figure 3. Earnings and FTFY are calculated specifically for women. 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-4 provides summary statistics, including means, standard deviations and the number of valid observations for each of these covariates.

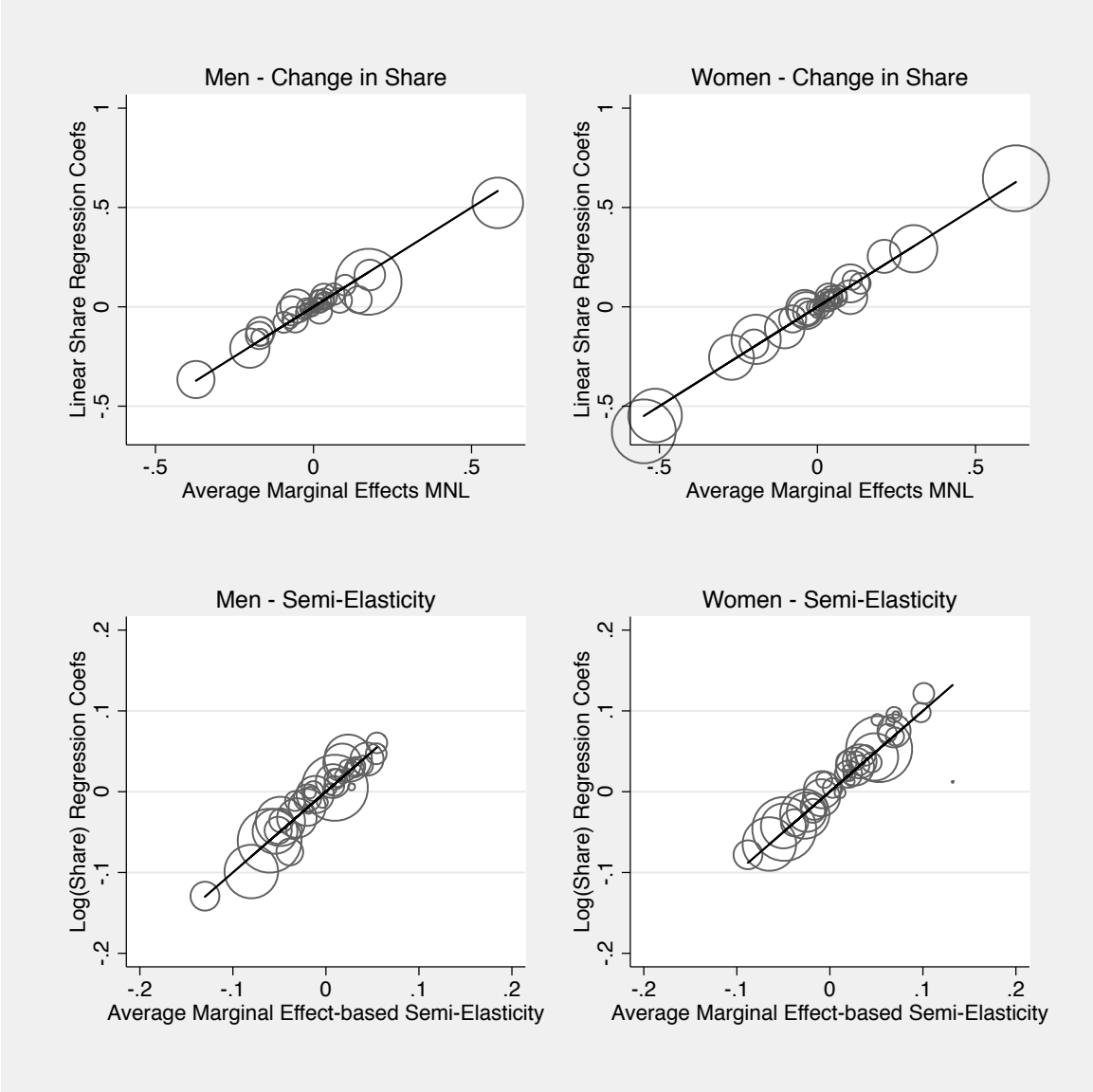
Table 3: Correlates of Cyclical Changes in Major Shares Among Men - Multivariate Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Median Log(Wage) Ages 35-45 - Men	0.170***	0.156***	0.125***	0.106***	0.123***	0.113***
	(0.0309)	(0.0377)	(0.0272)	(0.0252)	(0.0250)	(0.0310)
Number of Job Interviews w/in first year		0.00322	0.00567**	0.00286	0.00218	0.00466
		(0.00419)	(0.00271)	(0.00318)	(0.00314)	(0.00319)
Share in Unrelated Jobs in first year			-0.122***	-0.125***	-0.117***	-0.110***
			(0.0320)	(0.0336)	(0.0307)	(0.0383)
Long-run average Female Share of Major				-0.0532*		
				(0.0268)		
Average GPA for Major Courses					-0.113*	
					(0.0620)	
Share Working FTFY (35-45) - Men						0.127
						(0.189)
Constant	-0.596***	-0.567***	-0.415***	-0.304***	-0.0135	-0.478***
	(0.110)	(0.120)	(0.0919)	(0.0912)	(0.220)	(0.139)
Observations	32	32	32	32	32	32
R-squared	0.427	0.438	0.597	0.641	0.635	0.605

Robust standard errors in parentheses. *** p¡0.01, ** p¡0.05, * p¡0.1. 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) calculated among women as the dependent variable. These coefficient estimates are available in Figure 5. Earnings and FTFY are calculated specifically for men. 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-4 provides summary statistics, including means, standard deviations and the number of valid observations for each of these covariates.

Appendix - For Online Publication

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.

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.

Table A-2: Complete Set of Coefficient Estimates for Equation 7

	Men					Women				
	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	0.0403 ***	(0.0131)	0.160 ***	(0.0432)	0.041	0.0752 ***	(0.0073)	0.2540 ***	(0.0302)	0.031
Actuarial Science	0.0304	(0.0419)	0.002	(0.0012)	0.000	0.0121	(0.0884)	0.0026	(0.0022)	0.000
Agriculture	0.0301 **	(0.0115)	0.044 **	(0.0166)	0.016	0.0954 ***	(0.0234)	0.0430 ***	(0.0116)	0.007
Architecture	-0.0132	(0.0099)	-0.009	(0.0082)	0.010	-0.0012	(0.0289)	-0.0045	(0.0095)	0.003
Biology Fields	-0.0035	(0.0140)	0.004	(0.0679)	0.048	0.0024	(0.0095)	-0.0085	(0.0329)	0.040
Business Fields, not Finance	0.0048	(0.0067)	0.126	(0.1079)	0.188	0.0527 ***	(0.0089)	0.6468 ***	(0.1375)	0.126
Chemistry and Pre-Med	0.0313 ***	(0.0075)	0.064 ***	(0.0155)	0.020	0.0383 ***	(0.0112)	0.0405 ***	(0.0106)	0.010
Communications Fields	0.0131 *	(0.0074)	-0.022	(0.0265)	0.027	0.0375 ***	(0.0114)	0.0490	(0.0485)	0.033
Computer-Related Fields	0.0326 **	(0.0139)	0.036	(0.0820)	0.031	0.0979 ***	(0.0184)	0.1335 ***	(0.0326)	0.011
Early and Elementary Education	-0.0988 ***	(0.0162)	-0.073 ***	(0.0114)	0.009	-0.0648 ***	(0.0053)	-0.5468 ***	(0.0497)	0.083
Economics	0.0169 *	(0.0087)	0.051 *	(0.0256)	0.029	0.0683 ***	(0.0150)	0.0632 ***	(0.0138)	0.010
Education Fields, Other	-0.0607 ***	(0.0075)	-0.366 ***	(0.0449)	0.060	-0.0461 ***	(0.0062)	-0.6267 ***	(0.0844)	0.117
Engineering Fields	0.0469 ***	(0.0088)	0.523 ***	(0.1019)	0.111	0.1216 ***	(0.0204)	0.1180 ***	(0.0239)	0.013
Environmental and Natural Resource Fields	-0.0011	(0.0214)	-0.001	(0.0193)	0.009	0.0261	(0.0397)	0.0068	(0.0098)	0.004
Family and Consumer Sciences	-0.0357	(0.0218)	-0.005	(0.0039)	0.002	-0.0237 **	(0.0109)	-0.0327 *	(0.0175)	0.016
Finance	0.0292 *	(0.0153)	0.032	(0.0434)	0.026	0.0724 ***	(0.0183)	0.0467 **	(0.0198)	0.010
Industrial and Commerical Arts	-0.0116	(0.0188)	-0.012	(0.0174)	0.006	0.0325 ***	(0.0110)	0.0261 **	(0.0112)	0.011
Journalism	0.0070	(0.0174)	0.010	(0.0151)	0.009	0.0361 **	(0.0135)	0.0387 **	(0.0162)	0.011
Leisure Studies	-0.0481 ***	(0.0180)	-0.028 *	(0.0148)	0.008	0.0144	(0.0144)	-0.0016	(0.0124)	0.007
Liberal Arts and History Fields	-0.0326 ***	(0.0053)	-0.208 ***	(0.0313)	0.067	-0.0253 ***	(0.0037)	-0.1095 ***	(0.0160)	0.045
Literature and Languages Fields	-0.0491 ***	(0.0085)	-0.144 ***	(0.0260)	0.032	-0.0424 ***	(0.0097)	-0.2546 ***	(0.0577)	0.058
Mathematics and Statistics	0.0008	(0.0129)	-0.007	(0.0218)	0.017	0.0046	(0.0126)	-0.0087	(0.0138)	0.011
Natural Science Fields, Other	0.0604 ***	(0.0075)	0.109 ***	(0.0140)	0.019	0.0449 ***	(0.0101)	0.0527 ***	(0.0121)	0.012
Nursing	0.0414 **	(0.0158)	0.019 **	(0.0082)	0.006	0.0430 ***	(0.0090)	0.2921 ***	(0.0634)	0.065
Other Fields	0.0149	(0.0144)	0.008	(0.0180)	0.010	0.0125	(0.0302)	0.0013	(0.0109)	0.002
Pharmacy	0.0032	(0.0105)	0.003	(0.0057)	0.004	0.0889 ***	(0.0236)	0.0299 ***	(0.0087)	0.004
Physics	0.0315	(0.0211)	0.030	(0.0191)	0.008	0.0173	(0.0183)	0.0020	(0.0022)	0.001
Political Science and International Relations	-0.0078	(0.0138)	-0.020	(0.0528)	0.037	0.0217 **	(0.0089)	0.0491 **	(0.0195)	0.021
Pre-Law and Legal Studies	-0.0220	(0.0292)	-0.004	(0.0041)	0.002	0.0866 ***	(0.0295)	0.0188 ***	(0.0063)	0.002
Protective Services	0.0155	(0.0101)	0.028	(0.0234)	0.022	0.0371 **	(0.0141)	-0.0075	(0.0175)	0.012
Psychology Fields	-0.0368 **	(0.0142)	-0.123 **	(0.0485)	0.035	-0.0277 ***	(0.0084)	-0.1637 ***	(0.0594)	0.070
Public Affairs, Health, Policy	0.0202	(0.0173)	0.006	(0.0054)	0.003	0.0204 *	(0.0113)	0.0106 **	(0.0045)	0.004
Social Science Fields, Other	-0.0479 ***	(0.0126)	-0.078 ***	(0.0214)	0.019	-0.0385 ***	(0.0132)	-0.0610 **	(0.0248)	0.021
Social Work	-0.0746 *	(0.0424)	-0.009	(0.0077)	0.004	-0.0183 *	(0.0097)	-0.0252	(0.0194)	0.021
Sociology	-0.1293 ***	(0.0204)	-0.154 ***	(0.0228)	0.013	-0.0781 ***	(0.0162)	-0.1867 ***	(0.0408)	0.024
Technical Engineering Fields	0.0059	(0.0119)	0.031 **	(0.0135)	0.013	0.0952 ***	(0.0257)	0.0135 ***	(0.0031)	0.001
Technical Health Fields	0.0360 *	(0.0205)	0.047 *	(0.0266)	0.010	0.0311 ***	(0.0083)	0.1180 ***	(0.0322)	0.042
Visual and Performing Arts	-0.0194 *	(0.0109)	-0.065 *	(0.0355)	0.028	-0.0075	(0.0095)	-0.0191	(0.0360)	0.039

This table provides a complete set of coefficient estimates and standard errors used to construct Figures 5-4. 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.

Table A-3: Gender Differences in Major Cyclicality

	Men		Women		Difference		
	Coef		Coef		Coef	S.E.	
Accounting	0.0403	***	0.0752	***	-0.0349	(0.014)	**
Actuarial Science	0.0304		0.0121		0.0183	(0.106)	
Agriculture	0.0301	**	0.0954	***	-0.0653	(0.02)	***
Architecture	-0.0132		-0.0012		-0.0120	(0.024)	
Biology Fields	-0.0035		0.0024		-0.0059	(0.013)	
Business Fields, not Finance	0.0048		0.0527	***	-0.0479	(0.008)	***
Chemistry and Pre-Med	0.0313	***	0.0383	***	-0.0070	(0.014)	
Communications Fields	0.0131	*	0.0375	***	-0.0244	(0.01)	**
Computer-Related Fields	0.0326	**	0.0979	***	-0.0653	(0.017)	***
Early and Elementary Education	-0.0988	***	-0.0648	***	-0.0340	(0.013)	**
Economics	0.0169	*	0.0683	***	-0.0514	(0.016)	***
Education Fields, Other	-0.0607	***	-0.0461	***	-0.0146	(0.004)	***
Engineering Fields	0.0469	***	0.1216	***	-0.0747	(0.014)	***
Environmental and Natural Resource Fields	-0.0011		0.0261		-0.0272	(0.035)	
Family and Consumer Sciences	-0.0357		-0.0237	**	-0.0119	(0.026)	
Finance	0.0292	*	0.0724	***	-0.0432	(0.02)	**
Industrial and Commerical Arts	-0.0116		0.0325	***	-0.0442	(0.022)	**
Journalism	0.0070		0.0361	**	-0.0291	(0.014)	**
Leisure Studies	-0.0481	***	0.0144		-0.0625	(0.02)	***
Liberal Arts and History Fields	-0.0326	***	-0.0253	***	-0.0074	(0.005)	
Literature and Languages Fields	-0.0491	***	-0.0424	***	-0.0067	(0.007)	
Mathematics and Statistics	0.0008		0.0046		-0.0037	(0.014)	
Natural Science Fields, Other	0.0604	***	0.0449	***	0.0155	(0.013)	
Nursing	0.0414	**	0.0430	***	-0.0016	(0.016)	
Other Fields	0.0149		0.0125		0.0025	(0.042)	
Pharmacy	0.0032		0.0889	***	-0.0857	(0.025)	***
Physics	0.0315		0.0173		0.0142	(0.029)	
Political Science and International Relations	-0.0078		0.0217	**	-0.0295	(0.013)	**
Pre-Law and Legal Studies	-0.0220		0.0866	***	-0.1086	(0.047)	**
Protective Services	0.0155		0.0371	**	-0.0216	(0.015)	
Psychology Fields	-0.0368	**	-0.0277	***	-0.0092	(0.01)	
Public Affairs, Health, Policy	0.0202		0.0204	*	-0.0002	(0.019)	
Social Science Fields, Other	-0.0479	***	-0.0385	***	-0.0094	(0.01)	
Social Work	-0.0746	*	-0.0183	*	-0.0564	(0.039)	
Sociology	-0.1293	***	-0.0781	***	-0.0512	(0.024)	**
Technical Engineering Fields	0.0059		0.0952	***	-0.0893	(0.031)	***
Technical Health Fields	0.0360	*	0.0311	***	0.0049	(0.02)	
Visual and Performing Arts	-0.0194	*	-0.0075		-0.0119	(0.009)	

This table provides tests of the equality between genders of the Log(share) coefficients presented in Appendix Table A-2.

Table A-4: Descriptive Statistics for Correlates of Major Cyclicality

	N	Mean	Std. Dev.
ACS Variables			
Change in Log(Share) with 1 ppt unemp - Men	38	-0.00473	0.0417
Change in Log(Share) with 1 ppt unemp - Women	38	0.0240	0.0483
Share with Graduate Degree (Age 35-45)	38	0.349	0.134
Long-run average Female Share of Major	38	0.515	0.207
Share living in state of birth (Age 35-45)	38	0.518	0.0653
HHI of occupations (Age 35-45)	38	0.0733	0.101
Median Log(Wage) Ages 35-45 - Men	38	3.491	0.198
Share Working FTFY (35-45) - Men	38	0.827	0.0430
Median Log(Wage) Ages 35-45 - Women	38	3.322	0.189
Share Working FTFY (35-45) - Women	38	0.584	0.0572
B&B Variables			
Average GPA for Major Courses	33	3.321	0.0948
Average Math GPA	28	2.620	0.241
Number of Job Interviews w/in first year	32	5.550	1.605
Median SAT Math Score/100	31	5.352	0.470
Median Number of Math Credits	34	5.206	5.586
Share Employed at 1 year	34	0.859	0.0574
Share in Unrelated Jobs in first year	34	0.470	0.148

Source: Authors' calculations from ACS and B&B data. Each major receives equal weight in the calculations.The first two rows of the table 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.