Cashier or Consultant? Entry Labor Market Conditions, Field of Study, and Career Success[1]

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Abstract

We analyze outcomes of college graduates as a function of the economic conditions they graduated into and the skill requirements of their field of study. To this end, we combine multiple data sets with information on earnings and field of study for U.S. college graduates graduating between 1976 and 2011. This provides coverage of multiple business cycles and larger sample sizes than the typical cohort-based analyses in this literature. We categorize college majors by indicators of skill in the majors, predominantly the average earnings premium. We then measure earnings, wage, employment, occupation skill level and educational attainment outcomes across graduation cohorts and major skill level. We find that early careers are disrupted by poor labor market conditions; a large recession at time of graduation reduces earnings and wages by roughly 9% and 13% (respectively) in the first year, and reduces the probability of full-time employment by 11 percentage points. These effects are fairly short-lived, fading out over the first five years of a career or so. We also find that the earnings gap across college majors widens in recessions; a typically high-earning major increases his or her earnings advantage by a third when graduating in a bad recession, and this effect remains large in magnitude for the first seven years after college graduation. We find evidence of small, positive educational attainment effects among low-return majors graduating into a worse economy. We find no impacts on occupation quality. We also determine that differential cyclicality of college major cannot account for our findings. We compare our earnings and wage effects across recessions and find that overall earnings losses from poor entry conditions are substantially larger for graduates in the 2001 and 2007-09 recessions, and these earnings losses are more evenly dispersed across college majors.

1 Introduction

The impact of the Great Recession was widespread with unemployment rates doubling for nearly all subgroups of the population. Recent college graduates, whose unemployment rate increased from 9% in 2007 to a peak of 17.6% in 2009, were no exception. Research on previous recessions suggests this group will experience significant earnings losses over their careers, relative to their luckier counterparts who graduated just before or just after the recession.[1] Research also suggests that college graduates face sizeable earnings differences depending on their field of study.[2] A natural question then is how these returns will interact with the business cycle;who bares the brunt of the entry-conditions effect on earnings? Does an engineering student retain his or her roughly 50% earnings advantage above an education major, or even widen it when graduating into a recession? Or, does the general lack of opportunity compress these earnings differences?

College majors differ widely in the skill requirements of their degree and subsequent jobs. For example, Turner and Bowen (1999) show substantial variation in average SAT scores across college major and Arcidiacono (2004) shows that the ordering of majors by earnings is very similar to the ordering by relative SAT math score. It is also likely that training opportunities and skill appreciation will be more important for career paths in some majors than in others. Though the literature on the career effects of entry conditions is sparse on underlying mechanisms, Kahn (2010) does suggest human capital disparities as a likely driver. Consistent with this notion, effects are typically worse for higher human capital individuals where post-schooling skill accumulation is likely more important. For example, college graduates face larger, more persistent impacts than do high school graduates; white men experience worse wage outcomes than women and minorities.[3] We might therefore expect higher skilled majors, where training opportunities could be more important, to bear larger costs when entry conditions are worse.

However, students in more skilled majors have better labor market opportunities, regardless of the business cycle they graduate into. We might then think that higher skilled graduates can more easily weather a recession, downgrading into lower skilled jobs, if necessary, and crowding out their counterparts in other majors. They may also have the tools to recover more quickly from a poor initial job placement. Oreopoulos, von Wachter and Heisz (2012) find that higher-skilled graduates who enter the labor market in a recession catch up more quickly than their lower-skilled counterparts. They argue this is because the returns

[1] Kahn (2010) estimates that white men graduating in the worst part of the 1981-82 recession earned over 20% less, relative to those graduating in nearby peaks, and these effects persisted for 15-20 years. Oreopoulos, von Wachter and Heisz (2011) find somewhat similar effects on men in Canada over a twenty-year period , though magnitudes and persistence are somewhat weaker.

[2] For example, Altonji, Blom and Meghir (2012) show that earnings differences across college majors can be as large as the overall college-high school premium. See their paper for a survey of the literature on the returns to college major.

[3] See Kondo (2008) and Hershbein (2009). Also Oyer (2006) and (2008) show large consequences for MBA's and economics PhD's graduating into recessions.

to on-the-job search will be higher for this group, so they search with more intensity.

In this paper, we analyze short- and medium-term career outcomes of college graduates as a function of the economic conditions they graduated into and the economic return of their major. We combine seven data sets with information on earnings and field of study for U.S. college graduates, graduating between 1976 and 2011. Our pooled data yields coverage of multiple business cycles and larger sample sizes than the typical cohort-based analyses in this literature. We categorize our roughly 50 college major classifications by indicators of skill in these majors, predominantly the average earnings premium in the major and average SAT math score in the major. We then measure the impact of graduating in times of higher unemployment across these skill groups for a range of labor market outcomes over the first thirteen years of a career.

We first analyze annual earnings and find, consistent with the previous literature, significant earnings losses to graduating from college in times of higher unemployment. Initial earnings decline by roughly 2.3% in response to a one percentage point increase in the unemployment rate at college graduation and the effects partially persists for the first several years of a career. This result is consistent with that found in Oreopoulos et al. (2012) and a bit smaller and less persistent than that found by Kahn(2010). .We also find that high-earning and high-skill college majors increase their earnings advantage when the unemployment rate is high. A four percentage point rise in the graduating unemployment rate (a large recession during our time period) raises the initial return to college major by almost one third in our preferred specification, and this effect also persists for several years into a career. That is, the negative effect of graduation into arecession is substantially smaller for high-skill majors. Our point estimates suggest that a major whose earnings premium is two standard deviations above the mean suffers no earnings loss when graduating in a period of higher unemployment, while a major two standard deviation below the mean would suffer a 5% drop in initial earnings per point of unemployment. This result is generally robust to the use of different measures of college major skill and also to the inclusion of a range of control variables.

We next analyze several additional labor market outcomes, including employment, wages, and occupational and educational attainment. We find no evidence that the graduating unemployment rate impacts the probability of being employed and no differential differential effects across college majors. This is perhaps not surprising given the overall high likelihood that a college graduate is employed. However, we find substantial differences in the probability of working full-time; workers graduating into a 1 percentage point higher unemployment rate are 2.6 percentage points less likely to work be working full time in their first year out, though this effect does not persist past the first two years after graduation, and here again we find no evidence of differential impacts across college majors. Also, we find sizeable negative impacts of graduating into a recession on wage rates, but again no differential impacts across college major. Furthermore, when we restrict earnings to full-time workers, the negative effects of graduating in a recession are about half as large and statistically insignifcant, and the differential effect across college majors is only half as large as in the full sample. We find no impacts on occupational attainment; graduates in worse economies end up in similar occupations in terms of average returns and average skill level, and this is true regardless of major. Taken together, these results suggest our earnings effects are driven by a combination of impacts on hours and on earning power, though we lack the precision to decompose these effects further. Finally we examine educational attainment and find small negative impacts for those graduating in worse overall economies. This is surprising given the opportunity cost of further schooling is lower for this group, however our effects are small and a bit noisy.[4] We do find that educational attainment is more negatively impacted by a recession for higher skilled majors. For a large recession (4 ppt increase in the unemployment rate), majors whose earnings return is two standard deviations above the mean will obtain a third of a year less schooling, relative to the average graduate in a recession.

It is also possible that higher skilled majors go into industries and occupations where labor demand is more cyclical. This could explain our earnings and employment results and is plausible since the literature on cyclical upgrading finds that employment in higher paying industries is more cyclical than that in lower paying industries (Bils and McLaughlin 2001). To examine this mechanism, we construct a major-specific graduation unemployment rate by averaging occupation-specific unemployment rates in the Current Population Survey data using estimates of the occupational distribution of each major. We indeed find a negative correlation between skill level and cyclicality of the major-specific unemployment rate, but it is small. A one standard deviation increase in skill level of the major reduces its cyclicality by only 6 percent relative to the average major. Furthermore, directly controlling for the major-specific unemployment rate does not change our primary coefficients of interest, although the unemployment measures are noisy.

The business cycle could also differentially impact majors if some majors typically enter into a narrower set of occupations. If some sectors are more impacted than others by a recession, then some jobs will be difficult to enter into when graduting into a recession. We construct a Herfindahl index for the distribution of occupations each major typically enters into in order to estimate the labor market return and interaction with the business cycle of being in a more specific major. We find majors in a more concentrated set of occupations fare worse when graduating into a recession, relative to those who typically move to a more diverse set of jobs. This is interesting and intuitive. However, we find this specificity measure is only weakly correlated with our other measures of major skill. Therefore it cannot help us account for our earnings and employment effects.

Finally, we present evidence that the earnings impact of entry conditions varies over the

[4] Most research has focused on the impact of local labor market conditions on high school completion and college enrollment. In addition, Kahn (2010) shows that students graduating in the worst part of the 1981 recession obtain a year of graduate school, on average, relative to those graduating in the best times.

time period we study, with graduates from the 2001 and 2007-09 recessions experiencing much larger, and more persistent, earnings and wage losses than graduates from prior recessions. For example, wage losses for those graduating into a recession are twice as large for post-1997 graduates than for those graduating before, and the difference in earnings is even larger. In addition, we find that the impacts of recessions in the more recent period appear to be more broad-based; our estimates show almost no differential impact across college majors over this time period. In future drafts, we will investigate whether these differential effects are driven by the nature of the business cycle in each period—specifically whether the sectoral shocks in each recession differentially impact labor demand across college majors.

Our work is most closely related to Oreopoulos et al. (2012), who use Canadian university-employer-employee matched data to study the earnings effects of graduating in times of higher unemployment, and how these effects vary with the skill level of the graduate. They find smaller and less persistent effects for workers who went to better schools, majored in more difficult subjects, and received better grades. They find this group is able to catch up more quickly through upgrading on firm quality. Our result that higher skilled majors fare relatively better when graduating into a worse economy is entirely consistent with their work. We offer the first results on this question for the United States across a long time horizon with large sample sizes. We also show our results are robust to a number of different college major categorizations. In addition, we can measure a number of other outcomes, such as employment and educational attainment, that were unavailable in the administrative dataset used by Oreopoulos et al. Though we cannot measure firm quality in our data, we use O*Net task measures and occupation earnings differentials to assess the quality of jobs workers are entering into over the business cycle and across college major.

This paper proceeds as follows. Section 2 discusses mechanisms via which bad labor market conditions at time of graduation could have persistent impacts on a career and why these impacts might differ across college major. We discusses our data sources and some measurement issues in section 3 before describing methodology in section 4. Section 5 presents our core results on earnings, wages and employment, occupational and educational attainment, the impact of controling for cyclicality and specificty of the major, and some distributional impacts. In section 6 we summarize our findings on the heterogeneity of these effects across recessions. Section 7 concludes.

2 Mechanisms

In this section, we explore potential mechanisms through which labor market entry conditions could impact workers' careers and why we might expect these impacts to be differential across college major.

The literature on entry conditions suggests that those graduating into recessions will start in lower level jobs and spend more time in unemployment (Devereux 2002).[5] We might think that a typically highly mobile young worker (Topel and Ward 1992) could recover from this setback, if slightly more gradually in the face of search frictions. Even this will result in differential speed of recovery if some workers exert a greater search intensity than others. Shimer (2004) points out that the expected return to job search will positively impact search intensity, and Oreopoulos et al. (2012) hypothesize that differential search intensity is driving their result that higher skilled majors catch up relatively quickly when graduating into a recession. Furthermore, Wozniak (2010) finds that the geographic location choices of college graduates are more sensitive to local labor conditions than are those of high school graduates. This suggests higher skilled workers are more adaptible to unlucky conditions, perhaps because they exert greater search effort. A pure search theoretic framework will predict a sluggish recovery that is in direct proportion to the inhibiting effects of search costs. If search costs are small then we should not see lasting labor market effects to graduating into a recession, but we might see differential effects across groups based on their expected returns to search or adaptibility. In particular this mechanism would suggest that higher skilled majors with greater adaptibility and likely greater returns to search will fare relatively better when graduating into a recession.

However, a number of factors suggest poor entry conditions will result in a longer setback. A poor early start could put college graduates in jobs with fewer training and promotion opportunities, resulting in a lasting disadvantage.[6] This disadvantage could easily be differential across college major if some majors suffer greater mismatch between their degree and the opportunities for advancement in their starting jobs when graduating into a recession. We might think that for higher skilled majors, post-schooling human capital accumulation is more important, suggesting they would suffer more from these effects. But this is actually an open question. Furthermore, time spent in unemployment or underemployment could be more damaging to some majors if skill depreciation is more rapid or ports of entry are more important. For example, Oyer (2006 and 2008) finds long-term earnings loss for economics Ph.D.'s and MBA's (respectively) graduating into worse economies and these effects are operate almost entirely through initial industry placement (entry into an academic job or the finance industry, respectively).

Majors who tend to enter into only a specific set of jobs will likely be more at risk of experiencing negative consequences due to skill depreciation associated with graduating into a recession. For example, accounting majors may only have a narrow range of jobs they can go into that take advantage of their skill set. A worker from a major that typically

[5] One motivation for the former effect is found in the cyclical upgrading literature (e.g., Bils and McLaughlin 2001), which finds that higher paying industries are more sensitive to the business cycle. Matches occuring in a recession are therefore likely to be found in lower paying industries and individuals must work their way up as the economy recovers.

[6] For example, Gibbons and Waldman (2006) derive a model with task-specific human capital. Workers entering firms in worse economies start out in lower levels and therefore never accumulate as much task-specific human capital in the more important jobs.

sends students to a more diverse set of jobs, such as political science, could very well have an easier time weathering the recession.[7] Furthermore, recessions will differ in the type of sectoral shocks experienced. This means some recessions will hit college graduates harder than others and these impacts will be differential across degree type. For example the 2001 recession was driven in part by the "dot com" bust. This shock to the information technology sector surely resulted in larger impacts to college graduates overall and to those coming from technical majors, more specifically.

A poor early start due to a recession also results in a murkier signal of worker quality, since perspective employers cannot update as much based on the worker's first job. This could then inhibit the assortative matching process that should occur as firms learn about worker quality (Gibbons, Katz, Lemieux, and Parent 2005), leaving unlucky recent graduates lagging behind. Finally, a series of papers finding evidence of persistent firm-level entry cohort effects (for example Baker, Gibbs, and Holmstrom 1994, and Beaudry and DiNardo 1991) suggest a role for contracting rigidities, such wage insurance or bargaining based on outside options and imperfect mobility. We have only limited ability to consider these more contract theoretic explanations, due to data limitations, though we do find them interesting.

In sum, then, we would expect persistent career effects of gradauting into a recession if search costs are very high or if training and promotion opportunities become limited after a poor early start. These effects might be differential across college major. We speculate that higher skilled majors may be better able to adapt to a poor early start through greater job search intensity, but also may be more damaged by a lack of human capital advancement opportunities and even worse impacts skill depreciation. We do not have a strong prior about the relative effects of contracting rigidities on high skilled majors.

Finally, in this section we would like to discuss the interpretation of our results and whether they can be seen as uncovering a causal relationship between economic conditions and labor market outcomes and the interaction with college major. The impact of entry economic conditions on labor market outcomes is arguably exogenous since it is unlikely that students optimally time their graduation date (see Kahn 2010 for more on this). However, choice of college major is certainly correlated with the ability to succeed in the labor market (see for example Arcidiacano 2004, among others). In that sense our paper simply reports heterogeneity in the effect of entry conditions across an observable characteristic. We do not wish to attribute a causal relationship between major choice and the ability to weather an economic downturn, but we think in a descriptive sense, any heterogeneity we find is quite interesting in its own right. A larger problem for our interpretation would be if students choose their college major in response to the business cycle, since this would yield differential selection into some college majors over the business cycle. Blom (2012) does find that students' major choice respond to aggregate economic conditions at age 20; she finds students

[7]By our measure, accounting is the second most specific major, while political science is among the least specific. See Appendix Table 5 for a complete listing of majors.

shift to higher-return majors when economic conditions are worse. Thus we might worry that unobserved ability within college major varies over the business cycle. This suggests that if anything high-return majors are negatively selected when graduating into a recession than into a boom, working against our finding that high return majors fare relatively better. A countercyclical increase in the relative supply of high return majors would also bias our estimates down. Furthermore, the correlation between age 20 unemployment rate and age 22 unemployment rate (when the modal student graduates) is 0.37 over our sample period. This implies that there is still substantial independent variation in graduation conditions, even controling for earlier conditions. We hope to examine this directly in future work. In a future draft we also hope to examine observables across college majors in different cohorts to see whether there is any evidence of differential selection.

3 Data and Sample Characteristics

3.1 Data Sources

In order to estimate the short- and medium-term effects of initial economic conditions on labor market outcomes across college major, with coverage over several national expansions and contractions, we pool multiple data sources: the National Longitudinal Survey 1972 (NLS72), the National Longitudinal Survey of Youth 1979 (NLSY79) and 1997 (NLSY97) cohorts, the National Survey of College Graduates for 1993 (NSCG93) and 2003 (NSCG03), the Baccalaureate and Beyond 1993 (BB93) and 2008 (BB08) cohorts, the Survey of Income and Program Participation (SIPP)'s 1984 through 2008 panels, and the American Community Survey (ACS) from 2009, 2010, and 2011.[8] By pooling these data sets and restricting our attention to college graduates, we observe workers who graduated from college between 1976 and 2011 with labor market outcomes measured from 1977 to 2011.[9] Appendix table 1 reports this coverage by survey. To better align the length of time individuals can be observed since college graduation across data sets, we restrict our attention to workers between ages 22 and 35 and those who are between 0 and 13 years out of college. We also exclude workers who graduated before age 20 or after age 24 (roughly 3% of the sample, mostly from late graduates).

These surveys are chosen because they contain information on both college major and labor market outcomes. In all but the SIPP we can easily classify college major into 51 categories; this set of majors is commonly used by the Department of Education. The SIPP has one classifcation of 20 categories in panels 1984-1993 and another with 18 categories from 1994-2008. We explain how we use and combine these variables in the next subsection.

[8] We do not use the 1985 SIPP panel, which does not have college major information, or the 1989 SIPP panel, which was abandoned and did not produce enough follow-up waves to be useable.

[9] Though we have data on college graduates from 1971-75, the samples are small in those years, and are therefore lost when we apply cell-size restrictions, described below.

In all surveys but the ACS and the NLS72, we can determine the exact year of college graduation. For the ACS we assume that each respondent graduated from college at age 22, the most common graduation age in our other data sets.[10] In the NLS72, we infer the year of graduation from questions in each wave about years of college completed.[11] We provide a brief description of each survey next and details of specific variable creation in the appendix.

The NLSY79 is a panel dataset that follows 12,686 respondents who were aged 14 to 22 in 1979. Respondents were surveyed each year from 1979 to 1994 and biennially thereafter; we use data through 2000. College graduates in this survey graduated between 1979 and the late 1980s, a period that included a severe (but short-lived) recession in the early 1980s. The NLSY97 is similar in design to the NLSY79. The almost 9,000 respondents were aged 12 to 16 in 1996 and have been surveyed every year since 1997 and through 2010. These cohorts graduated from college between 2000 and 2009, a period that included a shallow recession in 2001.

The NSCG93 and NSCG03 are cross-sectional data sets made up of samples of 148,905 and 100,402 workers, respectively. The sample frame are those who reported having a college degree in the previous decennial census (1990 and 2000, repsectively). These data sets each yield one year of labor market outcomes for a range of college graduation cohorts. Given our age restrictions, workers in our NSCG93 sample graduated from college between 1976 and 1990, a period containing two recessions. The NSCG03 sample graduated between 1986 and 2000, a period containing the 1991 recession.

The BB93 consists of about 11,000 students who graduated from college in 1993. These workers are surveyed in 1994, 1997, and 2003, providing three observations per worker in this cohort. The BB08 is composed of about 19,000 college graduates from 2008, who are surveyed in 2009. Because each BB covers only one cohort, neither survey on its own provides variation in economic conditions at the time of graduation. Instead these surveys provide cross-sectional variation in college major, and help estimate our control variables within cohort.

The NLS72 is a panel survey of about 16,000 high school seniors in 1972, with the bulk of eventual college graduates graduating in 1976. We exploit two waves of the survey with post-graduation information (1979 and 1986), and use some of the previous waves to calculate year of college graduation. In these latter waves, a subset of the sample (roughly 40%) is asked for job and pay information in the intervening years. Because these workers are in a single high school graduation cohort, the NLS72 provides little variation in economic conditions at the time of graduation. Thus the same caveats apply here as those described

[10] We also take advantage of quarter of birth information in the ACS. For those born in the first half of the year we impute graduation year to be birth year plus 22. For those born in the second half of the year, we impute graduation year to be birth year plus 23, since they would have been 22 in May of that year.

[11] Due to the sampling design, we cannot perfectly assign year of graduation for a subset of respondents in the NLS72. We assign graduation year to be the first year in which the respondent says he has at least four years of college.

with the BB data sets.

The SIPP is a series of two-, three-, and four-year panels covering the period from 1984 to 2012. Each worker is surveyed three times per year during his or her panel's stay in the sample and provides monthly data on employment, earnings, hourly wages, enrollment, and other key variables. Combining all the panels of SIPP together, we have about 60,000 person-year observations. During the second wave of each panel (the second interview, which covers the preceding four months), respondents also complete an education history module which includes information on highest degree, year of bachelor's degree, and field of degree.[12] Respondents in SIPP in our restricted age range graduated between 1971 and 2008, and we have earnings observations from 1984 to 2011.

The ACS consists of repeated cross-sections covering roughly 2 million households in each of 2009, 2010, and 2011, by far our largest data sets.[13] Our age restrictions leave us with respondents who graduated from college between 1996 and 2010, covering a period with two booms and two busts.

Our measure of initial labor market conditions is the unemployment rate for the year in which the worker graduated from college; we use annual measures given by the BLS to reduce noise in both the measure itself and that which would be generated from our inability to pinpoint the exact month of graduation in some surveys. While the unemployment rate is an imperfect indicator of labor market conditions, it is highly visible and is the most commonly-used measure in prior work; Kahn (2010) and Oreopoulos et al. (2012) show that both the national and local-level unemployment rates at time of college graduation have strong relationships with worker outcomes. Our main set of results exploits variation in the national unemployment rate, whichis probably the more relevant one for college graduates, though we do discuss robustness to using a regional unemployment rate (for the four Census regions, the most disaggregated location we can obtain in some of our data sets).[14]

To provide a sense of sample coverage, appendix table 2 presents counts of the number of observations in the pooled sample by value of the graduation unemployment rate and years since graduation (hereafter potential experience). As one can see, we have substantial numbers of observations at both low and high levels of unemployment. However, it is also clear from the table that the pooled data is heavily skewed towards low unemployment rates. This is because the ACS is much larger than our other data sets and its graduates tend to be from low unemployment years (with the exception of the most recent graduates from these surveys who graduated into the Great Recession). This feature of our data leads us

[12] The education module is not included in the 1985 panel, and therefore we do not use that panel. From 1984 to 1993 (excluding 1985), panels only ask for field of highest degree rather than field of bachelor's degree. We therefore only use respondents in those panels with exactly a bachelor's degree. From 1996 forward, the survey asks for field of every degree received, including the bachelor's degree. We therefore use all workers with at least a college degree from 1996 forward.

[13] The ACS program began in 2001 but has only included field of bachelor's degree since 2009.

[14] Using unemployment rates for the region of degree also introduces additional noise because in some data sets we do not know the location of college graduation and instead have to use the current location.

to employ a two-step estimation procedure that will allow us to put equal weight on each graduation year-potential experience cell. We describe the procedure in more detail in section 4. While the nature of labor market shocks surely varies over time, we find it interesting to characterize the overall impact of graduating into a period of high unemployment across the long time period spanned by our data sets. If we were to estimate our regressions on an unweighted sample, then our results would be primarily driven by the recent period. We chose our two-step estimation, described below, to avoid this. However, in section 7 we discuss how the effects of early labor matket conditions vary over time.

3.2 Labor Market Outcome Measures

Our primary outcome of interest is annual earnings. This measure is useful in that it captures the full effect of labor market entry conditions, incorporating both impacts on earnings power and on work hours. Our measure of annual earnings varies across survey and we describe the details of our variable creation in the data appendix.[15] Because of these differences across surveys, we always control for survey fixed effects, and we experiment with a number of additional controls. We adjust earnings to 2006 dollars using the Consumer Price Index. We also restrict the earnings sample to workers earning at least $500 (in 2006 dollars) and exclude all observations where the worker reports being enrolled in school. To reduce the influence of high-earning outliers, we topcode annual earnings at $400,000. Furthermore, because of our inability to time both the date of college graduation and the date of the interview in the ACS, we exclude earnings measures in the year of college graduation, beginning the earnings sample with those one year out of school.

To understand whether any earnings differences we find are driven by effects on hours, or differences in earnings power, or both, we define indicator variables for whether the worker was employed, and whether the worker was employed full-time; we also define a pay rate measure.[16] For each of these variables we exclude enrolled workers. We further restrict pay rates to be between $5 and $250 per hour by top- and bottom-coding at those values.[17]

We also construct an occupation quality measure to determine whether any differences in pay are driven by differential access to high quality jobs. Using the ACS, we regress log

[15]The NLSY79, NLSY97, and ACS contain the variable annual earnings in the prior calendar year or prior 12 months. The SIPP contains monthly earnings measures which we sum over a calendar year then divide by the number of months with earnings measures. The NLS72 has wages in the current or most recent job, which we multiply by reported hours in that job. Finally, the NSCG's and the BB's have a measure of annual salary in the current job.

[16]In general, these variables are taken as a snapshot at the time of the survey. For SIPP, however, employment and full-time status are defined as the fraction of months during the year the worker was in that state during the year. Full-time is defined as 35 or more hours per week except in the NSCG, which only asks if the worker was full- or part-time. Pay rate is measured as the hourly rate of pay if one is available or can be created, or as annual salary if hourly wages and hours worked are not available. For more detail see the data appendix.

[17]In the data sets for which we must use annual salary instead of hourly wage, we recode high values as $400,000 to be consistent with our earnings results.

earnings on worker characteristics and occupation fixed effects (using 1990 Census codes for all data sets)[18] for full-time workers aged 25 to 59. We take these occupation fixed effects as our measure of occupation quality. We have also experimented with a similar measure based on industry.

Finally, to determine whether labor market conditions impact educational attainment, we analyze whether the worker is enrolled at the survey date and the highest grade completed at the survey date.[19]

In Table 1 we report weighted summary statistics, calculated by assigning equal weight to each graduation year-potential experience cell. This most closely describes our regression sample, where we will employ a two-step weighting procedure, described below. The top panel of the table refers to the earnings sample (those with at least $500 in earnings who are not enrolled in school). In the bottom panel we report the means of the dependent variables (pay rate, employment, fulltime employment conditional on earnings, highest grade completed, and enrolled in school) for the corresponding samples in each analysis. Average annual earnings in our data is about $46,000 in 2006 dollars. We top-code earnings at $400,000 to reduce the influence of outliers. The average graduation year is 1990 and the average year of an earnings observation is 1997. As noted above, these surveys yield subtantial variation in the national unemployment rate at time of graduation when we pool them together; the national unemployment rate at graduation ranges from 4.0% to 9.7%. Among non-enrolled people, the sample we use to study employment and work hours, 89% of people were employed, and 85% of those with a valid earnings observation were employed full-time (or 77% of the non-enrolled sample) About 15% of our full sample was enrolled at the time of the survey.

For comparison purposes, appendix table 3 reports unweighted summary statistics with the same sample restricitons. There the average graduation year is 1998 and the average earnings observation year is 2005, both relatively late in the time period we study, reflecting the size of the ACS. The ACS also skews the average unemployment rate at graduation to be quite low but with large variation. This table makes clear that our weighting procedure is necessary to balance the data across time.

3.3 Characteristics of College Majors

A primary goal of this paper is to estimate the differential effects of labor market conditions across college majors. In principle, we could estimate a separate effect for each of our 51 major categories, but that quickly becomes intractible. Instead we categorize our majors

[18]See the data appendix for details on occupation crosswalks.

[19]These are straightforward in most of our data sources. The NSCG 1993 and the 1984 wave of SIPP do not have enrollment information, and this variable is coded as missing for those surveys. In the other SIPP waves, enrollment is defined as the fraction of months the worker was enrolled during that year. The 1984-1993 SIPP panels only contain field of bachelor's degree for workers without an advanced degree, and thus advanced degrees are excluded in those panels.

along a number of continuous dimensions and report how these measures interact with entry conditions. A more detailed discussion of how we create our major-level variables is in the data appendix.

Our first such measure is the earnings return to each major. We pool our data sources (excluding SIPP) and estimate a log earnings regression on worker characteristics, as well as survey, year, and major effects.[20] This regression is estimated only for full-time workers between the ages of 36 and 59; this importantly excludes the sample we use to estimate the effect of entry conditions on labor market outcomes, avoiding any simultaneity concerns. For the SIPP, we mentioned above that we have two separate, more aggregated major classifications, corresponding to the early panels (1984-1993) and the later panels (1996-2008). We therefore estimate a similar log earnings regression in each of these samples to obtain major fixed effects for the SIPP categories. In each of the three separate regression samples, psychology is the excluded major category. We then pool all three sets of major fixed effects together and standardize them to have a mean zero and standard deviation one. We denote the standardized fixed effects as β^{major}, and use these as our primary characteristic of interest. We will therefore estimate the differential effect of entry conditions across majors with different labor market returns.

We also construct the average SAT math score within each major (hereafter SATM).[21] This can be constructed with our BB panels since they contain test scores for individual respondents.[22] To use these variables in the SIPP analysis, we must create a crosswalk from each SIPP category to the 51 Department of Education categories. We construct these crosswalks based on intuition and report the mapping in appendix tables 4a and 4b. In this table we also report the share of observations in a Department of Education major category across the set of majors that map to a given SIPP category using our pooled data (where we allow the shares to differ by gender). We then create the average SATM in a SIPP category by taking a weighted average of the test score means from our Department of Education majors, using these reported shares as the weights.[23] These test score variables are then also standardized to mean zero and standard deviation one. They are indicators of the quality of students in the major and perhaps the difficulty of the coursework.

Another major quality measure we use is a proxy for the skill level required in the occupations that a particular major tends to go into. For this we exploit O*NET task measures for occupations and merge these with the ACS at the 1990 Census code three-digit level. Via principal component analysis, we obtain the primary factor from a set of O*NET

[20]The worker characteristics we use in this regression are gender, race, and region dummies, and a cubic in potential experience.

[21]Our results are also robust to using an SAT-ACT composite measure instead, though we do not present those in the paper. We choose instead to focus on SAT math score because it has a much sronger relationship with future earnings than does the SAT verbal score.

[22]We pool the BB93 and BB03 cohorts and estimate the average test score of each major using sample weights.

[23]We also note that our results using $\beta^{major}$are robust to creating a similar measure using this crosswalk.

measures associated with critical thinking and problem solving. This measure is highly correlated with earnings.[24] We aggregate this measure to the major level by averaging its values across occupations within a major in the ACS samples. [25] This yields a measure of the general quality of occupations that students from each major go into. We hereafter term this variable "LOGIC", an apt descriptor of the task measures used. This variable is mapped into SIPP major codes following the same procedure as that used for SATM.

We are also interested in how the specificity of a major's possible career paths may affect outcomes. If a major tends to move into a diverse set of occupations then perhaps this major will be somewhat sheltered in times of high unemployment. We therefore construct a Herfindahl index to measure the specificity of each major in terms of the distribution of occupations its students typically enter.[26] A higher value of this index signifies a more "specific" major, whose students enter a more concentrated set of occupations.[27] We also map this into SIPP using the same mapping procedure described above. In our sample, major specificity is slightly positively correlated with β^{major}, the economic return to the major ($\rho = 0.08$).

We will also make use of a major-year-specific demand measure to understand the extent to which the business cycle differentially impacts the occupations a given major typically enters into. We first create a major-occupation mapping using our pooled (non-SIPP) sample for workers age 26-59, yielding the distribution of workers within a given major across occupations. We then measure annual unemployment rates at the occupation level using the CPS March Supplement.[28] Using our major-specific occupation distributions we then generate a weighted sum of unemployment rates at the major-year level. We again use the same major-category mapping procedure to obtain these variables for the SIPP. We will use this major-demand variable as a control in some of our specifications to determine whether differential labor demand over the business cycle could be driving our results.[29]

Table 2 reports values of the major characteristics for a selected set of majors. (Appendix

[24]The specific set of task measures we use are the O*Net measures (both importances and levels) for critical thinking, analyzing data, complex problem solving, inductive reasoning, problem sensitivity, analytical thinking, operations analysis, systems evaluation, problem solving, deductive reasoning, and systems analysis.

[25]We use only the ACS (as opposed to our pooled sample) because they provide the largest sample sizes, by far. A pooled analysis would heavily weight the ACS anyway.

[26]We obtain the fraction of students in a given major that go into each three-digit occupation, for workers 36 to 59, in our pooled data. Then we sum the squared fractions within the major. For more detail, see the data appendix.

[27]Nursing is the most specific major in our data, while "other social sciences" is the least specific major.

[28]We define the unemployment rate as the number of unemployed people who report their most recent job was in the given occupation divided by this plus employment in the occupation.

[29]Major-specific unemployment rates are a funciton of both major-specific labor demand and the adaptability of workers in the major (i.e., the ability to find a job outside the typical fields they enter). Ideally we would use a measure that only includes the former effect, since the latter is more relatived to major specificity. To that end, we have also experimented with using major-speciifc employment levels. However, this measure is problematic since we cannot express it as a rate. For example, it is highly sensitive to how we detrend it.

table 5 provides the information for the full set.) The majors are sorted by β^{major}, the major specific earnings effect, with electrical engineering and economics at the top, and education and philosophy and religion at the bottom. Recall that all of the variables are standardized to a mean of zero and a standard deviation of one.[30] Therefore, the table reports that electrical engineers earn 1.57 standard deviations more than the average major, while philosophy and religion majors earn 2.41 standard deviations less than the average. One can see from the table that the β^{major} is strongly correlated with the average SATM (SAT math score) and with LOGIC (the task intensity of the occupations associated with a given major). Note that a few majors, such as nursing and philosophy/religion, are exceptions to the generally positive correlation between test scores and earnings. Philosophy majors have test scores well above the average major, but earn substantially less, while nursing majors have below-average test scores but are relatively high earners. The major specificity measure is shown in column 5. Note that nursing is by far the most specific major, while education majors also score highly. In contrast, social science and liberal arts majors tend to have low degrees of specificity.

4 Econometric Model and Methods

Our goal is twofold: to estimate the effect of the unemployment rate at graduation on labor market outcomes, and to estimate these effects differentially across college majors. We would like to estimate regression models of the following form.

(1)

$$Y_{ict} = \beta_1 X_{it} + \beta_2 U_c + \beta_3 U_c PE_{it} + \beta_4 U_c PE_{it}^2 + \beta_5 Z_i^m + \beta_6 Z_i^m PE_{it} + \beta_7 Z_i^m U_c + \beta_8 Z_i^m U_c PE_{it} + \delta_t + \epsilon_{it}.$$

In (1) Y_{ict} is a labor market outcome measured in year t, for an individual i, in college entry cohort c, such as log annual earnings, log wages, employment, occupation quality or educational attainment. U_c is our measure of labor market entry conditions, which we define as the deviation of the national unemployment rate from its sample mean of 5.8 percent in the year of college graduation. X_{it} is a set of control variables, including a quadratic in potential experience PE_{it}.[31] As noted above, we define PE_{it} as the number of years since college graduation, rather than actual labor market experience, which could be endogenously related to economic conditions at time of graduation. $Z_i^m$is a variable characterizing the major m chosen by individual i, including the earnings return to a given major (β^{major}) and

[30] Average SAT math score is non-disclosable for smaller majors due to confidentiality concerns. We follow the reporting convention of the public-use tables available on the Baccalaureate and Beyond website and omit these values from our table. However,they are included in our analysis.

[31] The full set of control variables we employ is survey fixed effects, year fixed effects, a quadratic in potential experience, gender, race, gender interacted with race and potential experience, and region of residence. We describe below that some of these will enter into the first step regression while others enter into the later step:

the average SAT Math score (SATM). The component δ_t is a fixed effect for the year when the outcome variable was measured; it controls for current demand conditions. We adjust the error term,ϵ_{it}, for a number of different correlation structures, described in more detail below.

Our two main coefficients of interest in this regression model are β_2, measuring the effect of entry conditions on initial labor market outcomes, and β_7, which measures the differential impact of entry conditions across a college major characteristic. To estimate the persistence of the the graduation-year unemployment rate effect, we interact it with a quadratic in potential experience. We have also estimated models with only a linear interaction in potential experience and find qualitatively similar results, but the quadratic seemed to be a better fit. For estimating degree of persistence in the differential effect of entry conditions across college major, a linear interaction with potential experience is adequate.

The data we have are less than ideal for estimating a regression model like (1). This is because, as noted above, our data are not balanced across time or across experience levels; instead, our pooled sample is heavily skewed towards more recent college graduate cohorts.[32] Since we want to estimate average effects of entry conditions on labor market outcomes over our entire sample period, we need to weight the data more equally across years; this is especially important if these effects change over time. In section 6, we directly investigate this issue by allowing for variation in these effects over time.

One way to estimate average effects over the time period we study is to weight each graduation year-potential experience cell equally. However, this method is accompanied by a large loss in efficiency, since it upweights noisy small cells and downweights precisely estimated large cells There is no way around some degree of inefficiency if we want equal weighting. However, we attempt to retain some of the precision given in our larger cells through a two-step estimation procedure, which we describe next.

4.1 Two-Step Estimation Procedure

Our goal here is to estimate a regression similar to that specified in equation (1), while equally weighting graduation year-potential experience cells but still retaining some of the extra precision our larger datasets provide. We therefore first estimate a regression of a labor market outcome on control variables, taking full advantage of our unweighted sample. We then collapse residuals to the major-graduation year-potential experience cell (or in our notation the mcp-level, where p is potential experience) and use these in a second step regression to estimate our coefficients of interest. In this second step regression, we weight the data so that the distribution of observations across college majors, m, in a given cohort, c, matches the empirical distribution, but each graduation year-potential experience cell, cp,

[32]As noted in the data section, the large ACS samples yield an abundance of low unemployment-high experience observations.

gets the same weight. Since the unit of observation in the second step is at the *mcp*-level, we are naturally worried that some cells made up of very few observations will have too large an influence. We address this concern in two ways. First, we exclude *cp* cells with fewer than 100 earnings observations to eliminate the influence of the smallest cells.[33] We also trim the data for extreme outliers using a procedure described in more detail below.

In step one, we regress the outcome variable (earnings, wages, employment, etc.) on *mcp*-cell fixed effects, as well as all control variables that are not collinear with the fixed effects – gender, race, region, race and gender times potential experience, and some of the survey dummies. We weight observations with survey weights and otherwise allow larger data sets to have more impact. From this regression, we obtain the estimated *mcp*-cell fixed effects.[34]

For step two, we first collapse the data to the *mcp*-level. We then regress the outcome variable on the control variables we did not use in the first stage, which include Z_i^m and its interactions, U_c and its interactions, δ_t, and the remaining survey dummies. Our main results tables report the results of these second-stage regressions. The number of observations for these regressions is the number of *mcp*-cells remaining after our cell size restriction.[35]

In order to equally weight across *cp*-cells, while maintaining the distribution of majors within a graduation year, we weight this regression by the number of observations in the *mcp*-cell divided by the number of observations in the *cp*-cell. We also trim the data to minimize the influence of outliers that are typically based on only a handful of observations. We take our collapsed data and regress the *mcp*-cell fixed effects on on the survey dummies that were not identified in stage one, year dummies, a quadratic in experience, the major variable, and the major variable interacted with experience. We obtain the residuals from this regression and trim cells in the top and bottom 2 percent.[36] We then estimate our step-two regressions as described above. Trimming does not significantly change our point estimates, but it improves our precision considerably.

A key decision we must make in our estimation is how to cluster standard errors. As we are interested in outcomes that vary at the graduation year (U_c), graduation year-potential experience (U_cPE_{it}), major-graduation year ($Z_i^mU_c$), and major-graduation year-potential experience ($Z_i^mU_cPE_{it}$) levels, no uniform method will do. Furthermore, the best choice of control variables also depends on the primary parameter of interest, and the choice of

[33] This restriction removes about 25,000 person-year observations, or 5.8% of our pooled, unweighted data, mostly from the early waves of the SIPP.

[34] We treat the early and late SIPP major categories as separate majors from the 51 B&B categories. This gives us a total of 89 majors.

[35] Some variables that we obtain for the Baccalaureate and Beyond major categories and then "map" to the SIPP major categories are missing in some cells and therefore have fewer observations. This is because there are three SIPP majors for which there is no B&B equivalent (vocational studies, liberal arts/humanities, and medicine/dentistry).

[36] We work with residuals rather than simply eliminating the bottom and top two percent of cell fixed effects to better isolate variation in the fixed effects due to sampling error from variation in majors, survey fixed effects, and the other variables we control for in this step.

clustering is connected to the choice of controls.

In our basic specification, we cluster at the graduation year level, the level of variation underlying U_c. Here we are primarily interested in the effects of U_c and its interaction with potential experience. In an augmented specification, we additionally control for major fixed effects, instead of the main effect of Z_i^m, to reduce the potential for bias, increase precision, and eliminate a source of serial correlation in the residuals. . In some of our specifications, we also replace the graduation unemployment rate $U_c$with graduation year fixed effects, to control for average differences across cohorts. This could potentially be quite important since we estimate parameters over a long time horizon (but of course the graduation year effects are not separately identifiable from main effect of U_c). In these regressions, we also include major fixed effects instead of the major variable Z_i^m. This is our preferred way of estimating the $(Z_i^m U_c)$ effects and their interactions with potential experience. In this case we report results with robust standard errors that simply account for heteroskedasticity at the cell level, as well as standard errors clustered at the major-graduation year level.

4.2 Other Estimation Details

The variables Z^m that characterize majors– major earnings, SATM, and others – are given in standard deviations for ease of interpretation and comparison. Importantly, this means that the main effect of the unemployment rate can be interpreted as the impact for the major with the average value of Z^m. We also exclude observations with zero potential experience in many of our regressions, because these observations will be influenced by months in school during the year of graduation. The interactions with potential experience that we report are actually interactions with potential experience minus one, so the coefficients on U_c and $Z^m U_c$are effects when potential experience is 1.

We experiment with a variety of alternative sets of control variables and report robustness of these in section 5.1..[37]Note that interpetation of our parameters is affected by the fact that entry unemployment rates are positively correlated with the unemployment rates at experience level 1 ($\rho = 0.76$) and experience level 2 ($\rho = 0.37$), so a worker leaving school in a recession is likely to experience more than just one bad year of labor market conditions. Since we do not control for unemployment rates between the time of graduation and t, the terms involving U_c will pick up the effects of variation in labor market conditions between c and t, conditional on the year dummies for t. Oreopoulos et al. exclude year dummies from their main analysis, in which case U_c captures association between $U_c$and labor market conditions between labor market entry and t. They also attempt to isolate the partial effect of U_c by controlling for the values of unemployment during the years between labor market entry and t. We intend to investigate this issue in a future draft.

[37]We exclude highest grade completed from our main specification because labor market conditions at entry may influence postgraduate studies, and instead examine that outcome separately in Section 5.6. However, controlling for highest grade completed makes very little difference.

5 Results for Earnings

5.1 Earnings Effects for β^{major}

Table 3 reports regressions from the second step of the estimation procedure for log annual earnings. There are six columns; the first two are targeted at understanding the main effect of the national unemployment rate at time of college graduation (U_c) on future earnings, while the next two focus on the interaction of U_c and β^{major}; we discuss columns 5 and 6 later. We therefore cluster standard errors in the first two columns by graduation year, the level of variation underlying U_c. Column 1 is our base specification while column 2 additionally controls for major fixed effects. Column 2 is our preferred specification for understanding the main effect of the national unemployment rate since we cluster at a conservative level and can control for arbitrary correlations within major for a given graduation year. In the third and fourth columns we further control for graduation year fixed effects. Though we can no longer identify the main effect of the national unemployment rate, this specification is useful in that it controls for arbitrary major effects and graduation year effects. Column 3 is our prefered specification for understand the entry effects across college major, where we report robust standard errors, while in column 4 we report a more conservative set of standard errors that are clustered by major-graduation year.

Column 1 shows that annual earnings fall by 0.023 log points in response to a one percentage point increase in the graduation-year unemployment rate. This effect is significant at the 10% level. This effect is almost identical in column 2, our preferred specification, as are the interaction effects with potential experience and its square. These interactions suggest that the impact of the entry unemployment rate does decline in magnitude over the first 7 years of a worker's career before leveling off then becoming more negative again. While we do not want to take this pattern of catch-up and subsequent divergence too literally, these results suggest that there is a modest negative earnings effect of graduating from college in times of higher unemployment that decays, becoming insignificant for most levels of experience. We take the estimates from column 2 and apply a large recession-size increase in the unemployment rate of 4 percentage points. These estimates suggest that in the first year after college graduation, earnings will be 9% lower for someone who graduates in the worst part of a bust compared to the best part of the boom. This effect decays to roughly 1.25% at 6 years out before increasing in magnitude in the later experience years.

Column 2 also suggests that the impact of graduating into a bad economy will be smaller for students in higher return majors. The coefficient on the interaction between $\beta^{major}$and the unemployment rate is positive and significant. To interpret these results we move to column 3, which includes graduation year fixed effects and is our preferred specification for estimating these interaction effects. The coefficient in row 6 implies that for a one percentage point increase in the unemployment rate, a major with a standard deviation larger earnings return will earn 0.0134 log points more. This effect is strongly statistically significant at the 1% level. The point estimate suggests that a major two standard deviations above the average major will see no earnings loss in a recession.

We can use the main effect of β^{major}, estimated in column 1 (before we included major fixed effects) to be roughly 17%, to characterize the magnitude of the $\beta^{major}U_c$ interaction. Again taking a large recession of a 4 ppt increase in the unemployment rate, we have a roughly 5.4% increase in earnings for a major with a one standard deviation higher β^{major} in a recession compared to a boom. Therefore the earnings advantage of a high-return major is amplified by an additional third (31%), when graduating in a recession compared to a boom. The interaction with potential experience suggests that this advantage slowly decays and is close to zero around 8 years after college graduation; however, even 7 years after graduation, the effect is significant at the 10% level. The results are similar in statistical significance when we cluster at the major-graduation year level (column 4), a conservative choice given we control for both major and graduation year fixed effects.

It is also worth noting that these results are robust to a number of additional control variables. Specifically, the inclusion of survey-graduation year fixed effects, survey-potential experience interactions, and β^{major}interacted with a cubic time trend do not change the point estimates, and actually improve the precision slightly.[38] Our results are also robust to the inclusion of educational attainment controls, though we prefer to omit controls that could be endogenously related to entry labor market conditions. Instead, we directly examine educational attainment as an outcome in section 5.5.

Table 3 therefore paints a consistent picture of a modest earnings disadvantage to graduating into a recession, but this effect is quite a bit smaller for workers in higher skilled majors. Our effects are quite a bit smaller and less persistent than those reported in Kahn (2010), who finds an initial decline in pay rates of more than 20% for white males who graduated in the worst part of the 1981-82 recession compared to those who graduated in the nearby booms; her effects diminish over time but remain significant well past 10 years out of college. We later discuss heterogeneity in our effects across demographic group and across recessions. Our results are much more in line with Oreopoulos et al. (2012) who exploit national and regional variation in labor market conditions in Canada over a 20-year period. They find a 1 ppt increase in the national unemployment rate at college graduation reduces earnings by roughly 2% in the first year out of college and this effect fades away by roughly 5 years. They also find that higher skilled graduates face smaller, less persistent earnings losses.

In appendix table 6, we present similar regressions on an unweighted sample in order to understand how sensitive our results are to the two-step estimation procedure. Since we do not have to weight, we can directly estimate the regressions specified in equation (1) These

[38]The time trend in β^{major} allows us to control for differences in the return to skills over time. The survey interactions are useful controls since our earnings measures vary slighly across surveys. These differences might be systematically related to experience and to labor market conditions upon graduating.

regressions produce main effects of the unemployment rate that are substantially larger in magnitude. They also show the interaction effects of $\beta^{major}$and the unemployment rate are smaller in magnitude and insignificant. Recall the unweighted regressions will heavily favor the ACS samples, which provide data for the years 2009-2011, and thus cover only the more recent college graduation cohorts. These unweighted results, then, are suggestive that there is some heterogeneity in the effects of entry conditions across business cycles; specifically, they suggest that recession effects may be both larger and more evenly spread across college majors in the more recent time period. We analyze this heterogeneity directly in section 6.

5.2 Earnings Effects for Other Characteristics of College Major

We next report log earnings regressions using our other characteristics of college major, discussed in section 3.3. Table 4 summarizes these regressions. We present two columns of results for each of three major-skill measures: SATM, LOGIC, and specificity. The first column for each measure is analogous to column 1 of Table 3 (allowing us to estimate the main effect of each measure in an earnings regression), and the second column for each measure is analogous to column 3 of Table 3 (our preferred specificaiton for estimating the interaction of major characteristic and U_c.

Results on the SATM measure, shown in columns 1 and 2, produce similar results to β^{major}, which is unsurprising since these measures are highly correlated. Our coefficient on the interaction between SATM and the unemployment rate from coluimn 2 is 0.012, highly significant at the 1% level. This interaction effect is actually larger relative to the return to a standard deviation increase in SATM of roughly 11%(reported in column 1), than we find for β^{major}. A large recession (a 4 ppt increase in the unemployment rate) will increase the return to a one-standard deviation larger SATM score by 44%. Also, the persistence of this effect is somewhat larger than the persistence of the β^{major}effect. Even at 7 years of experience, the interaction effect of SATM and the unemployment rate is positive (0.004) and significant at the 5% level.

Columns 3 and 4 report results for LOGIC, a measure of the analytic and problem solving intensity of the occupations typically associated with a given major. This factor has a return of about 12% per standard deviation (see column 3). However, the added effect from high unemployment is small and insignificant when we include major fixed effects in column 4. The 90% confidence interval for this coefficient ranges from -0.003 to 0.010, so we cannot rule out either a small negative effect or a substantial positive effect.

The final two columns report results using our specificity measure. We find this an interesting descripter in that it proxies for a lack of versatility in the major. Recessions may differentially impact occupations, reducing access to some more than others. If so, then a student from a major that typically sends workers to a narrower occupation distribution should perform relatively worse. This is exactly what we find. First, column 5 gives an indication of the labor market return to specificity, which we estimate to be a 0.048 increase in log annual earnings per one standard deviation in specificity, and decays linearly with experience. Interestingly, this effect is robust to excluding nursing, which has an extremely high degree of specificity and is a relatively well paying major.

Turning to column 6, we estimate how the return to major specificity varies over the business cycle. We find that a one-standard deviation increase in major specificity results in a decrease in earnings of 0.0066 when the unemployment rate increases by 1 ppt, significant at the 10% level. A large recession (a 4 ppt unemployment rate increase) then reduces the return to major specificity by 55%. The magnitude of this effect decays only slightly with experience, but quickly becomes insignificant. We will later investigate the extent to which major specificity can account for the earnings effects we find on β^{major}.

5.3 Earnings Effects for Regional Labor Market Conditions

To this point, our measure of entry conditions has been the national unemployment rate. This is because the national labor market is likely more relevant for college graduates, and since we cannot measure location of college degree in all data sets, a more local measure introduces additional noise. However, a more local measure yields additional cross-sectional variation that may help us identify our effects with more precision. In this section we present results using a regional unemployment rate (for four Census regions) in the graduation year, in place of the national rate.[39] When region at time of degree is unavailable, we use region of residence at the time earnings were measured.[40]

Appendix table 7 presents our results on regional unemployment rates. We find similar effects as those reported in table 3, our primary earnings specifications, but results are slightly smaller in magnitude. While a 1 ppt increase in the national unemployment rate lowered earnings by 0.023 log points, the corresponding effect of regional unemployment is a 0.019 point earnings reduction. This is as we expected; because the location choices of college graduates are more responsive to local labor market conditions relative to high school graduates (Wozniak 2010), the national market is likely the more relevant one for them. We also see a similar reduction in magnitude for the interaction with β^{major}. The table also shows that precision increases substantially when we use regional variation in the unemployment rate. The reduction in magnitude and increase in precision are consistent with Kahn (2010) who uses state unemployment rates and Oreopoulos et al. (2012) who use Canadian provinces. In the next draft, we hope to exploit the more disaggregated location information available in some of our data sets.[41]

[39] Region is the most disaggregated location information available consistently across data sets; however, some data sets contain much more disaggregated measures.

[40] Region of degree is unavailable for the ACS, SIPP, and NSCG 2003.

[41] For example, the restricted-access NLS data sets could be used to identify state of college graduation for most respondents.

5.4 The Role of Wage Rates Versus Employment and Hours

We next examine the extent to which the effects of labor market conditions at graduation operate through wage rates versus hours worked. Returning to table 3, our log earnings regressions using β^{major} as our major characteristics, columns 5 and 6 repeat our preferred specifications (columns 2 and 3, respectively) on a sample restricted to full-time workers. They account for 85% of the earnings sample. Column 5 shows that the main effect of the national unemployment rate is -0.011 (with a standard error of 0.0089), which is about half of the value in reported in column 2. Given the sampling error, we cannot rule out an effect of similar magnitude to that reported in column 2. The interaction terms with potential experience imply that the effects fully decay by 5 years out of college.

In column 6, we investigate the interaction effects and find these are also smaller in magnitude. A standard deviation increase in β^{major}corresponds to a 0.0059 increase in log earnings when the graduating unemployment rate is 1 ppt higher. This effect is about half the size of our estimate on the full sample and is only significant at the 10% level. However, our estimate is again imprecise and we cannot rule out an effect of the size of that reported in column 3.

Taken together, these results suggest that about half of the overall earnings effects of U_c operate through work hours effects. This leaves about half for effects on wage rates, but this decomposition is imprecise. We next analyze employment and full-time employment, and wage rates directly and find mixed support for this conclusion.

Table 5 reports results on employment (columns 1 and 2), full-time employment (columns 3 and 4), and log pay rates (columns 5 and 6). We restrict these analyses to non-enrolled observations and the full-time analysis to those in the earnings sample. Looking first at the probability of being employed, we find almost no impact of the national unemployment rate on its own or interacted with β^{major}. Column 1 shows that in the first year after college graduation, a 1 ppt increase in the graduating unemployment rate is associated with a 0.0052 ppt increase in the probability of being employed. A positive coefficient here is counterintuitive, but we note it is small in magnitude and statistically insignificant. In fact a 90% confidence interval implies that we could rule out effects outside the range of -0.0019 to 0.012, still fairly small considering the sample mean employment of 89%. Column 2 shows a small, insignificant effect of 0.0016 on the interaction of the graduating unemployment rate and β^{major}. Further, we can rule out an effect the size of 0.0042 with 90% confidence, again a fairly small impact. Though not reported here, the main effect of β^{major} on the employment probability is also a very small 0.0047 (with standard error 0.0034).

In contrast, columns 3 and 4 show that the probability of full time work is impacted by the graduating unemployment rate. Recall this sample is restricted to those with a valid earnings observation, so we can attempt to account for the earnings effects reported above. Here we find a 1 ppt increase in the graduating unemployment rate is associated with a 2.79 ppt decline in the probability of working full time, significant at the 1% level. A large recession of a 4 ppt increase in the national unemployment rate would result in an 11 ppt reduction in the probability of full-time employment. This effect is substantial, considering the sample mean of 85%. In our data, the gap in average earnings of full and part-time workers is more than 1.0 log point, so the reduction in full time could account for a substantial effect on average earnings for all workers combined. This result then supports the notion that early earnings differences are at least partially driven by hours effects, primarily on the intensive margin. However, the full-time employment effects decay rapidly, reaching zero by 3 years out of school. These effects are then a bit less persistent in magnitude than the earnings effects.

Column 4 shows the effect of the unemployment rate across β^{major}. The point estimate of 0.0030 (and a standard error of 0.0027) is small in absolute terms and statistically insignificant. However, it is 10% of the main effect of β^{major} , which we find is 0.028 though do not report in the table. We thus cannot rule out a sizeable impact on the probability of being employed full-time, conditional on having earnings, given the lack of precision in our estimates.

The first 4 columns of table 5, taken together, suggest that a substantial part of the main effect of the national unemployment rate on earnings may be operating through its effect on work hours. The evidence also suggests that hours effects account for part of the differential earnings effect across college major. However, precision limits what we can say. We next analyze pay rates directly. Columns 5 and 6 in table 5 report the analagous preferred specifications for the dependent variable of hourly pay rate, or current salary, depending on what is available in a given survey.

Here, the results are a bit puzzling. Since we saw the earnings differences across graduation cohorts fell in half when restricting to the full-time sample, we might also expect small impacts on pay rates. Instead, the effect of entry labor market conditions on wages seems to be slightly larger in magnitude than its effect on earnings. Column 5 reports that a 1 ppt increase in the graduation-year unemployment rate reduces starting wages by 0.033 log points. This effect is halved after 3 years but is still significantly at the 1% level. A large recession would then reduce earnings for recent graduates by 13% before decaying to around 1.5% at 7 years out. These effects are about half the magnitude of those reported by Kahn (2010), who focuses on wage rates instead of earnings.

Thus we find that the graduating unemployment rate has a sizeable impact on both earnings power and full-time employment. In column 6, we show that this is fairly uniform across β^{major}. The coefficient on its interaction with the graduating unemployment rate is small (0.003) and insignificant. However, the 90% confidence interval includes in its range a more sizeable 0.009 effect. Thus we again have too little precision to pin down an effect across college major.

In this subsection, we have provided evidence that the graduating unemployment rate impacts both earnings power and the probability of full-time employment. However, the respective contributions of each are unclear since we find large direct effects on the probability of being employed full-time and relatively small effects on earnings when restricted to the full-time sample, but also large effects on pay rates. It is also likely that both margins contribute to differential business cycle effects across college major; we find the earnings effect is halved when restricting to the full-time sample and we cannot rule out sizeable impacts on the probability of full-time employment and on pay rates.

5.5 Other Potential Mechanisms

In this section, we investigate other possible channels to explain the earnings effects we presented in section 5.1. We begin with an exploration of the quality of jobs recent graduates obtain as a function of entry conditions. We then explore whether the distribution of occupations a particular major typically enters into can account for our earnings effects, either because they it is narrower or because it is more sensitive to the business cycle. Finally, we estimate the educational attainment effects of graduating into a worse economy.

5.5.1 Effects of Labor Market Conditions on Occupational Attainment

Devereux (2003) and others have provided evidence that in weak labor markets employers upgrade the quality of the workers that they hire in a given occupation. This suggests that higher skilled workers will fare relatively better when graduating into a recession, taking away job opportunities from lower skilled workers. But it also suggests that these higher skilled workers will be forced to take lower quality jobs, given a general lack of opportunities. As we noted in section 2, if search costs are large or occupation specific human capital is important, negative effects on early occupational attainment may persist. Here, we investigate the impact of early labor market conditions on occupation quality. As described in section 3.2, we use occupation fixed effects from an earnings regression as our quality measure.

In the first two columns of table 6, we report results from regressions with our occupational quality measure as the dependent variable. Here we restrict only to workers who are not enrolled, and we do not condition on having sufficient earnings. Column 1 is our preferred specification for estimating the main effect of U_c , while column 2 summarizes our preferred specification for estimating the interaction effects withβ^{major} . Column 1 shows that the main effect of U_c on occupation quality is a precisely-estimated 0. The 90% confidence interval ranges from -0.004 to +0.004, both small effects relative to the impact of U_c on log earnings and log wages, and relative to the standard deviation of our occupation quality measure of 0.32. We also see a similarly small and insignificant coefficient on the $U_c\beta^{major}$ interaction; the 90% confidence interval for this coefficient falls in the even narrower range of -0.004 to 0.00093.

Interestingly then, occupation quality cannot account for differences in earnings across graduation cohorts or differences in the impact of graduating into a recession across college majors. This is true despite the fact that occupational return is an important part of the average return to college major. The coefficient on β^{major} in table 6 suggests that a one standard deviation increase in major quality is associated with an increase in occupational quality of 0.145 log earnings points. Recall that the coefficient on β^{major}in the earnings regression (Table 3) was 0.174. Therefore, 83% of the earnings return to college major is accounted for by access to higher-paying occupations. [42]

5.5.2 Occupational Specificity of Majors

We next examine whether the occupational specificity of a major is in part responsible for the positive coefficient on $\beta^{major}U_c$ in the earnings regression. Above, we showed that the college majors that typically work in a narrower distribution of occupations fare worse when graduating into a recession. Our specificity measure (a Herfindahl index of occupation dispersion within college major) is only slightly negatively correlated withβ^{major}, so is unlikely appriori that it could be a partial driver of our earnings effects. We investigate the possibility by including both β^{major} and major specificity in our standard earnings regression. Results are reported in table 6. Column 3 reproduces column 3 of table 3, our preferred specification for estimating interaction effects of β^{major} with the national unemployment rate. Column 4 additionally controls for major specificity interacted with the unemployment rate. (The main effect of major specificity is absorbed in the major fixed effects.) The coefficients on $\beta^{major}U_c$ and its interaction with potential experience are basically unaffected. We conclude that differential specificity in the occupation distribution across college major is an unlikely driver of the differential earnings responses to U_c across college major.

5.5.3 Differences Across Majors in the Cyclical Sensitivity of Demand

While specificity does not explain our earnings results for β^{major}, another factor that is worth exploring is any differential sensitivity to the business cycle across college major. For instance, some majors may see their demand rise and fall with overall conditions, while some may be relatively insensitive. To address this, we will include our major-specific demand measure (i.e., the major-specific unemployment rate in the year of graduation, hereafter U_c^{major}) as a control variable in our basic earnings regression. If the differential effect of business cycles on college majors is due to different major-specific labor demand – that is, if the unemployment rates of high-earning majors are less sensitive to overall economic conditions – then including this measure in the earnings regression (and its interaction with potential experience) may account for some of the positive coefficient on $\beta^{major} * U_c$.

[42] Using the 171 major categories available in the ACS in a log wage equation, Altonji et al. (2012) report that the standard deviation of college major coefficients falls from 0.177 to 0.098 when detailed occupation controls are added. The corresponding values for women are 0.146 and 0.074.

First, to build intuition on U_c^{major}, we summarize its historical relationship with the national unemployment rate and β^{major}. Column 1 of Table 7 reports regressions of U_c^{major} on U_c, β^{major}, and $\beta^{major} * U_c$, over the time period 1971-2011, where an observation is a major-year. The coefficient onU_c of 0.44, suggests that the unemployme for college graduates fluctuates only about half as widely as that of the whole labor market. The coefficient on $\beta^{major}$is negative, implying that high-earning majors generally have lower unemployment rates. Both of these results are sensible. Next, the interaction term of -0.0275 indicates that when aggregate unemployment rises, labor demand conditions deteriorate relatively less for higher-earning majors.[43] Including a cubic time trend (column 2) yields nearly identical results and increases statistical significance of the interaction term from 5% to 1%. This negative coefficient, implying that the unemployment rates of high-skilled majors are less sensitive to the business cycle, could help account for their widening earnings advantage in recessions compared to booms.

However, given the very small magnitude of the interaction effect on major-specific unemployment (-0.0275), relative to the overall impact of the unemployment rate (0.44), we do not expect the measure to explain much of the earnings differentials. This is exactly what we find. Column 3 of Table 7 reproduces our preferred earnings regression for estimating the interaction of $\beta^{major} * U_c$(column 3 of table 3), which we found was 0.0134.[44] In column 4, we also include controls for U_c^{major} and its interaction with potential experience. As can be seen in column 4, the coefficient of interest (on $\beta^{major} * U_c$) is hardly changed with the inclusion of these controls. Therefore, this particular measure of major-cyclicality cannot account for our earnings findings. However, as we have noted, unemployment rates are difficult to interpret since they also reflect the ability of workers to find jobs outside their usual occupation paths or at lower levels. In the next draft we will explore other major-specific demand measures.

5.6 The Response of Graduate Education

Early economic conditions could also impact educational attainment. Faced with a weak labor market and a low opportunity cost, students who graduate into a bad economy may choose to enroll in graduate school.[45] Differences in educational attainment could affect earnings outcomes in at least two ways. First, it could alter the composition of college graduates in the labor force across the business cycle. Second, if students complete higher degrees more often in a bad economy, early earnings could be lower (as students work part-

[43]The negative coefficient could also reflect that higher earning majors are more versatile and are better able to avoid unemployment.

[44]Sample sizes are smaller than in table 3 because here we must exclude the SIPP major categories that cannot be mapped into Department of Education categories – since our major-specific demand measures are generated only for these categories.

[45]Note that we have excluded enrolled students in all regressions to this point, so that an enrollment effect cannot directly account for any of our prior results. However, we examine educational attainment directly as an outcome of interest in its own right. See Kahn (2010), Bedard and Herman (2008) and Johnson (2013) for previous analyses of the effects of the business cycle conditions on graduate enrollment.

time in the summer, say) and late earnings could be higher, as workers enjoy the return to an advanced degree.

Table 8 reports regressions for enrollment status and highest grade completed.[46] For enrollment, we estimate the effects for a sample of young workers only (age 22 to 26) since this group's enrollment choices should be most impacted by early labor market conditions. For highest grade completed, we exclude interactions of the main variables of interest with potential experience, since educational attainment is an outcome measure that cannot decline once achieved.

Surprisingly, it appears that the unemployment rate has a small negative effect on the probability of enrollment.[47] Additionally, there is no differential enrollment effect across high- and low-earning majors.

The highest grade completed results (which do not include potential experience interactions) show similar effects for labor market conditions. Though not shown in the table, we have estimated the main effect of β^{major} and find a one standard deviation increase is associated with 0.33 more years of schooling completed, when measured at the mean graduation unemployment rate. However, this differential effect is decreased by a higher unemployment rate. A large recession of a 4 ppt unemployment rate increase wipes out a quarter of the increased educational attainmnent seen in high-earning majors. This suggests that, while poor economic conditions do not induce workers to complete more school overall, they do alter the composition of who is remaining in school. In a bad economy, it is the lower-earning majors who differentially complete more schooling.

5.7 Distributional Effects

To this point, we have observed a modest negative effect of the unemployment rate at graduation on earnings, wages, and the probability of full-time employment. We have also observed that high-earning and high-skill majors perform relatively better when entry economic conditions are poor. That is, high-earning majors are less sensitive to entry labor market conditions. In this section, we investigate the distributional impacts of those earnings effects in two ways. First, we look at effects by gender. Second, we look at effects by earnings quantile. Both of these exercises are instructive for thinking about potential mechanisms for the effects.

Table 9 presents our basic earnings regressions, estimated separately for men and women. Two findings stand out here. First, the negative effect of graduating in a recession is larger and more significant for men, although the estimates are not terribly precise. Second, the

[46] The highest grade completed regressions exclude the early SIPP waves, for which we are only using those with exactly a college degree. The enrollment regressions exclude the NSCG 1993 and 1984 wave of SIPP, for which we do not have enrollment information.

[47] Using CPS data from 1994-2008, Johnson (2013) finds that graduate enrollment is counter cyclical for women and acyclical for men. He does not have data on college major.

interaction between β^{major} and the unemployment rate is very different for men and women. Women in high-earning majors suffer much smaller earnings losses than women in the average major; in fact, the point estimates suggest that for women in a major one standard deviation above the mean, there is no negative effect of graduating in a recession. For men, on the other hand, the coefficient on the interaction is estimated to be about zero. Therefore, our earlier results for $\beta^{major}$are being driven entirely by women, while the main effect of the unemployment rate is driven mostly by men.[48]

Next, we use quantile regressions to study effects across different points in the earnings distribution. For these regressions, we do not use the two-step procedure since it would be intracible to estimate our *mcp*-fixed effects in a quantile regression; instead, we estimate quantile regressions similar to that specified in equation (1) and weight each graduation year-potential experience cell equally.[49] Table 10 presents the results, which are striking. First, we see that the unemployment rate at graduation has a negative effect on earnings at all three quantiles we study, but the effects are much larger at the 10th percentile than the 90th. Second, the $\beta^{major} * U_c$interaction, shows large positive effects at the 10th percentile, a smalller effect at the median, and actually a small negative effect at the top.

6 Earnings Effects across Recessions

Summarizing our results to this point, for college graduates from the mid-1970s to 2010, we find modest negative effects of the graduation-year unemployment rate. We also find that the higher-earning college majors widen their advantage when graduating into poor economic conditions. In this section, we ask if these patterns have changed over time. Recall that in our unweighted earnings results (see appendix table 3) we found a main effect of the unemployment rate that was larger in magnitude than our two-step approach, while the coefficient on the interaction with β^{major} was much smaller in magnitude. The unweighted results are heavily skewed towards the more recent period due to the larger ACS sample sizes, suggesting graduates from recent recessions may in fact have a different experience. We have explored a number of different ways of dividing the time period but found the most important distinction was between the two most recent recessions and the period prior to them.

Table 11 reports results for earnings (columns 1 and 2) and pay rates (columns 3 and 4) from a new specification that allows for changes over time. Specifically, we interact all of our key explanatory variables with an indicator equaling 1 if the worker graduated in 1998 or later (labeled "After" in the table).[50]The main effect of the unemployment rate now

[48]Part of the difference between men and women in the $U_c\beta^{major}$ interaction may be driven by the fact that we estimate β^{major} on a pooled sample of men and women. In a future draft we will estimate β^{major} for men and women separately.

[49]These results are not clustered; we hope to change this in a future draft.

[50]Results in this section are qualitatively similar for a range of cutoff dates around 1998. We do find it

gives the average effect for those graduating before 1998. To calculate the effect for post-1998 graduates one should add the interaction of the after dummy and the unemployment rate. The difference between the pre-1998 and post-1998 period is dramatic. For earnings, column 1 shows that the main effect of U_c is essentially zero for the earlier period, while in the later period earnings fall by about 8 percent per point of unemployment – 3.5 times our core results from table 3. This suggests that the two recent recessions have hit college graduates much harder than prior recessions did. The interactions with potential experience suggest that persistence is a bit lower for this group, with the effect fading out by 4 years of experience. But we cannot measure higher experience earnings for the recent cohorts. Column 3 shows that for wage rates, U_c does have a negative effect in the pre-1998 period of a roughly 2.5% decrease in earnings for a 1 ppt increase in the gradauting unemployment rate. But the interaction with after suggests that this effect doubles in magnitude in the post period.

The earnings effects of the unemployment rate by college major are equally striking. In the pre-1998 period (the interaction of β^{major} and U_c), high-earning majors suffer smaller earnings losses when the unemployment rate at graduation is higher; earnings increase by 0.03 for each standard deviation higher β^{major} and percentage point increase in the unemployment rate – more than double our previous estimate. In contrast, the effect is near zero in the post-1998 period. That is, in the post-1998 period entry conditions have a much larger, negative impact on career outcomes, and these effects are fairly evenly dispersed across high- and low-earning majors. Wage rate results reflect a similar pattern.

There are a number of reasons why the recent period may be different. First, the industries impacted by recessions have varied over time. Employment losses in the 1981-82 recession were disproportionately drawn from manufacturing, as were those in the 1991 recession which also saw sizeable employment losses in construction. Therefore college graduates in these recessions may have been somewhat sheltered. While manufacturing losses were also important in he 2001 recession so were job losses in information technology stemming from the "dot com bubble" burst. This recession may have therefore been fairly costly for college graduates and in particular higher earning college graduates. The 2001 recession was accompanied by the "tech bubble" burst which would have impacted technical, more educated fields. The Great Recession of 2007-09 was notoriously broad-based, impacting almost every sub group proportionately. College graduates were not sheltered in this recession and the finance industry in particular saw large losses. These two recent recession may then have leveled the playing field across education groups and within college graduates; that is, college graduates bore something closer to their "fair share", relative to non-college workers,

useful to include both the 2001 and the 2007-09 recession years in the later period, but results are robust to restricting the later period to 2004-2010. In principle we could have also estimated regressions on separate samples for an early and a late period. We prefer to stay with the pooled sample and interact only our key variables with the after-1998 dummy so that we maintain our ability estimate the other control variables precisely.

and the same was true for higher-earning majors relative to lower-earnings majors.

7 Conclusion

In this paper we estimate the labor market consequences of graduating from college in times of higher unemployment, and we test for differential effects across college major. We find that early careers are disrupted by poor labor market conditions; a large recession at time of graduation reduces earnings and wages by roughly 9% and 13% (respectively) in the first year, and reduces the probability of full-time employment by 11 percentage points. These effects are fairly short-lived, fading out over the first five years of a career, or so. We also find that the earnings gap across college majors widens in recessions; a typically high-earning major increases his or her earnings advantage by a third when graduating in a bad recession, and this effect remains large in magnitude for the first seven years after college graduation. Effects are similar for a range of major-characteristics. Standard errors are wider than one would like, but we obtain similar and somewhat more precise estimates when we exploit regional variation in labor market conditions.

Other than impacts on time spent working, we find the mechanisms we explore cannot help to account for the differential impact of entry conditions across college major. Occupation quality appears unaffected by poor entry conditions. This is in contrast to work by Oyer (2006 and 2008) who finds that economics Ph.D.'s and MBA's suffer long-term consequences of graduating into worse economies because of the persistence of their initial occupation and industry placements. Instead, we find that initial placements are less impacted by early conditions and any impacts that are present initially do not persist.

We show that the unemployment rates of higher paying majors are less sensitive to the business cycle; however, this effect is too small to account for the differential impacts on earnings. Future work should investigate the industry-occupation composition of economic shocks. We also find only small impacts on educational attainment. Higher skilled majors are relatively less likely to obtain years of graduate education when graduating into a recession and low skilled majors are relatively more likely. This is consistent with the differential opportunity cost of working during a recession that we estimate in our earnings regressions.

Our results fit well with the previous literature. We are quite consistent with Oreopoulos et al. (2012), who study labor market shocks in Canada and find modest earnings effects of graduating in a recession that persist for a few years and are smaller in magnitude for higher skilled majors. Our effects on the national unemployment rate are smaller in both magnitude and persistence, compared with Kahn's (2010) analysis of the 1981-82 recession. Besides studying a broader set of demographic groups (Kahn restricts her analysis to white males) we also study a much longer time horizon. We find an important role for heterogeneity in the effect of entry conditions across recessions; the 2001 and 2007-09 recessions had much larger impacts on recent graduates. We estimate that wage losses were twice as high in this period as the 1976-1997 period and earnings losses were 3.5 times larger. In addition, we find that in the later period, the impacts were much more uniform across college major. It looks as though the "modernrecession" is more broad-based, impacting recent college graduates and high-skilled majors to a greater extent than we find for previous recessions. An interesting direction for future work would be to better understand the types of shocks that lead to persistent (and differential) impacts on recent college graduates. This may yield a better understanding of the nature of recessions and recoveries of the last two decades.

What can explain the differential impacts of entry conditions across college major? It could be that since lower skilled majors spend more of their early experience years out of full-time employment, they suffer more from skill depreciation. However, we expected lower skilled majors to be less sensitive to this depreciation. It could instead be that high skilled majors can more easily recover from early setbacks because of more productive job search. This seems unlikely, however, since we do not find significant differenes in the rate of catch up across college majors. Also, we see no evidence that graduates suffer from poor early placements in terms of job quality. This suggests little scope for differential job upgrading over the recover. Of course we admittedly cannot measure firm quality. Finally, it could very well be that high skilled majors are just better. They have higher test scores, take harder classes, work in higher quality occupations, and earn more money. Perhaps then this type of worker also does better in a recession. However, this result is somewhat surprising given that these higher skilled workers have far more to lose.

References

[1] Altonji, Joseph G., Erica Blom, and Costas Meghir (2012) “Heterogeneity in Human Capital Investments: High School Curriculum, College Major, and Careers,” Annual Review of Economics, Volume 4. 185-223.

[2] Arcidiacono, Peter (2004) “Ability Sorting and the Returns to College Major,” Journal of Econometrics, Volume 121, No. 1-2. 343-375.

[3] Baker, George, Michael Gibbs, and Bengt Holmstrom (1994) “The Wage Policy of a Firm,” Quarterly Journal of Economics, Volume 109, No. 4. 921-955.

[4] Beaudry, Paul, and John DiNardo (1991) “The Effect of Implicit Contracts on the Movement of Wages Over the Business Cycle: Evidence from Micro Data,” Journal of Political Economy, Volume 99, No. 4. 665-688.

[5] Bedard, Kelly, and D.A. Herman (2008) “Who Goes to Graduate/Professional School? The Importance of Economic Fluctuations, Undergraduate Field, and Ability,” Economics of Education Review, 27, 197–210.

[6] Bils, Mark, and Kenneth J. McLaughlin (2001) “Interindustry Mobility and the Cyclical Upgrading of Labor,” Journal of Labor Economics, Volume 19, No. 1. 94-135.

[7] Blom, Erica (2012) “Labor Market Determinants of College Major,” Mimeo, Yale University. Devereux, Paul (2002) “Occupational Upgrading and the Business Cycle,” Labour, Volume 16, No. 3. 423-452.

[8] Devereux, Paul (2002) “The Importance of Obtaining a High-Paying Job,” Mimeo.

[9] Gibbons, Robert, and Michael Waldman (2006) “Enriching a Theory of Wage and Promotion Dynamics Inside Firms,” Journal of Labor Economics, Volume 24, No. 1. 203-207.

[10] Gibbons, Robert, Lawrence F. Katz, Thomas Lemieux, and Daniel Parent (2005) “Comparative Advantage, Learning, and Sectoral Wage Dynamics,” Journal of Labor Economics, Volume 23, No. 4. 681-724.

[11] Hershbein, Brad J. (2012) “Graduating High School in a Recession: Work, Education, and Home Production,” The B.E. Journal of Economic Analysis & Policy, Volume 12, No. 1, Article 3.

[12] Johnson, Matthew T. (2013) “The impact of business cycle fluctuations on graduate school enrollment”, Economics of Education Review, Volume 34. 122–134.

[13] Kahn, Lisa B. (2010) "The Long-Term Labor Market Consequences of Graduating from College in a Bad Economy," Labour Economics, Vol. 17, No. 2. 303-316.

[14] Kondo, Ayako (2008) " Differential Effects of Graduating During Recessions Across Race and Gender," Mimeo.

[15] Oreopoulos, Philip, Till von Wachter, and Andrew Heisz (2012) "Short and Long-Term Career Effects of Graduating in a Recession." American Economic Journal: Applied Economics, Volume 4, No. 1. 1-29.

[16] Oyer, Paul (2006) "Initial Labor Market Conditions and Long-Term Outcomes for Economists," Journal of Economic Perspectives, 20. 143-160.

[17] Oyer, Paul (2008) "The Making of an Investment Banker: Macroeconomic Shocks, Career Choice, and Lifetime Income," The Journal of Finance, 63. 2601-2628.

[18] Shimer, Robert (2004) "Search Intensity," Mimeo.

[19] Topel, Robert, and Michael P. Ward (1992) "Job Mobility and the Careers of Young Men," Quarterly Journal of Economics, Volume 107, No. 2. 439-79.

[20] Wozniak, Abigail (2010) "Are College Graduates More Responsive to Distant Labor Market Opportunities?" Journal of Human Resources Volume 45, No. 4. 944-970.

8 Data Appendix

Here we describe how certain variables that we use are created in the various data sources. The structure is as follows. First, we describe how we create our major earnings measure, other major-level variables, the occupational earnings measure, and various control variables. Then, for each data source, we summarize how we create or obtain our employment, enrollment, earnings, rate of pay, and graduation year variables.

The major earnings measure is created in most of the data (which have 51 major categories) and separately in the early and late SIPP data (which have fewer major categories). For each of the three sets of data, we regress log annual earnings on controls (gender, race, region, potential experience, and year dummies) and major fixed effects, with psychology the excluded category in each data source. The major fixed effects are the major earnings measure. We standardize it to be mean zero and variance one after combining the data sources. This regression is performed on those aged 36 to 59 to avoid estimating this on our main sample.

The SAT math measure is the average SAT math score for each major in the two waves of the Baccalaureate and Beyond (using the survey weights). Since we have this at the 51-major level, we obtain it for the SIPP using our own B&B-to-SIPP major crosswalk. The SIPP-level SAT math measure for a major, then, is the weighted mean of the B&B measures that map into that SIPP major, where we allow the weights to depend on gender.

Another major-level measure, the specificity of the major, is also obtained at the B&B-major level and then mapped into the SIPP. For this variable, we pool the non-SIPP data and get the fraction of people in each major that go into each occupation. Then within each major, we sum the squared fractions to create a Herfindahl index. This measure is also obtained using only those age 36 to 59.

The O*Net "logic" measure is obtained using principal components analysis in the ACS. The primary factor pulled from occupation data is highly correlated with earnings in the occupation. The mean value of this factor by major is the measure we use at the major level. Again, this is mapped into the SIPP data using our crosswalk.

We also create three major-year specific demand measures: the major-specific unemployment rate by year and the major-specific detrended employment by year. For these measures, we obtain the measure at the occupation level from the March CPS and then use a major-occupation mapping from the ACS and NSCG. The occupation-specific unemployment rate is straightforward. For employment, we regress the log employment on a quadratic (for one measure) and cubic (for the other) time trend and the unemployment rate. We then add the residual from that regression to the unemployment rate times the estimated coefficient on the unemployment rate. These variables are also created at the B&B major level and then mapped to the SIPP using our crosswalk.

Race/ethnicity is in three categories: Hispanic, black non-Hispanic, and other non-

Hispanic. We control for the four Census regions (West, Northeast, Midwest, and South). Potential experience is defined as year minus bachelor's degree graduation year.

Now we describe how we create a few of our outcome measures in each data source: annual earnings, rate of pay (wage), employment, enrollment, highest grade completed, full-time status, and occupational earnings. The occupational earnings outcome measure is defined as follows. Using the ACS, we regress log earnings on controls (including level of education) and occupation fixed effects. The occupation fixed effects are the occupation earnings measure. We use consistent 1990 Census coding for occupations across data sources, taking advantage of the coding scheme made available by Ruggles et al (2010).

Our first data sources are the NLSY79 and NLSY97. Annual earnings are taken from a direct question about wage and salary earnings in the prior year, while the wage measure is the hourly rate of pay in the current or most recent job. Employment and enrollment are "snapshots" at the time of the survey. Full-time is defined as working 35 hours or more per week at the current job. Highest grade completed is taken from a direct question each year. The occupation in the current job is used for the occupational earnings measure.

In the National Survey of College Graduates, annual earnings and wages are the same measure: annual salary in the current job. No separate earnings and wage measures are available, and we also do not have hours to create our own measures. Employment and enrollment are measured at the time of the survey, although the 1993 survey does not contain an enrollment variable, so that variable is marked as missing for that survey. While we do not have hours measures, we do have a question asking if the worker works full- or part-time. Highest grade completed and occupation are taken from direct questions.

In the Baccalaureate and Beyond 1993/03 and 2008/09, we also use annual salary as both our earnings and wage measure. Hours per week, employment, and enrollment measures are used for the relevant variables. Highest grade completed and occupation in the job at the time of the survey are taken from direct questions.

The NLS72 gives us the starting and ending/current wage in the most recent job. We take the average of those wage measures for our wage measure. We multiply that wage measure by annual hours to get the earnings measure. Employment, enrollment, and occupation are at the time of the survey. Highest grade completed is based on a direct question.

The ACS's earnings measure is total wage and salary income in the past 12 months. Unfortunately, we do not know when the respondent was interviewed, and thus we do not know if the earnings refers mostly to the prior year, to the current year, or equally to both. We thus follow the ACS's own reporting practices and assign the earnings as current-year earnings, rather than prior-year earnings. To construct wages in the ACS, we divide the annual earnings by the product of weeks worked in the prior 12 months and usual hours per week. The other variables are straightforward to define in the ACS.

Perhaps the most complicated data source for our variable definitions is the SIPP, because the data are monthly rather than annual. We begin by "excluding" months in which the worker is enrolled in school. We define annual earnings as the average monthly earnings for non-enrolled months times twelve. An hourly rate of pay measure is available, but only for the minority of workers who are paid hourly. Instead, our wage measure is earnings divided by total hours (all measured only in non-enrolled months). Employment is the fraction of non-enrolled months the worker worked at least one week, and full-time is defined analogously. Enrollment is the fraction of months the worker was enrolled (note: in the 1984 panel, enrollment information is not available). The occupational earnings measure is difficult to define here, because a worker may have many occupations in a year. We identify an occupation for each month, and the annual occupational earnings measure is the simple average of those twelve occupation's earnings measures. Highest grade completed is not hard to define, but the structure of SIPP presents a couple of problems. First, the early SIPP panels (1984 to 1993) only contain field of bachelor's degree information for workers with exactly a bachelor's degree. We therefore lose workers with an advanced degree for these years. Second, because education information is asked early in the panel, it is likely that we are missing some college graduates in the early years of their careers. For instance, a worker in the 2008 panel, which has information through 2011, who graduated in 2009, would not show up in our data, because he did not have a degree at the time of the education module.

Year of college graduation is straightforward to identify in most of our data sources. However, no information about time of degree is included in the ACS. To deal with this, we assume that all ACS college graduates graduated at age 22, which is the modal age of graduation in our data. We use the quarter of birth information from the ACS to find the graduation year. For workers born in the first half of the year, the year of graduation is birth year plus 22, so that the worker turns 22 in the spring before graduating in May or June. For workers born in the second half of the year, graduation year is birth year plus 23; that is, the worker would be 22 when he graduates, and would turn 23 later that year.

Table 1: Summary Statistics for Earnings Sample
with Equal Weighting across Graduation Year-Potential Experience Cells

Variable	n	Mean	St Dev	Min	Max
Male	399,886	0.48	0.50	0	1
Black	399,886	0.06	0.25	0	1
Hispanic	399,886	0.04	0.20	0	1
Potential experience	399,886	6.35	3.55	1	13
Graduation year	399,886	1990.28	8.69	1976	2010
Graduation unemployment rate (%)	399,886	6.39	1.43	4.0	9.7
Year	399,886	1996.63	8.96	1977	2011
Current unemployment rate (%)	399,886	6.32	1.54	4.2	9.7
Annual earnings (2006 $)	399,886	46,162	32,923	501	400,000*
Log annual earnings	399,886	10.51	0.76	6.22	12.90
Employed	399,886	0.96	0.17	0	1
Highest grade completed	399,886	16.40	0.90	16	20
Summary Statistics for Relevant Samples					
Employed	454,116	0.89	0.30	0	1
Full-time	399,886	0.85	0.33	0	1
Enrolled	132,703	0.22	0.37	0	1
Occupational earnings	426,534	-0.71	0.32	-1.61	0.04
Highest grade completed	534,315	16.41	0.90	16	20

Notes: Primary sample includes non-enrolled workers age 22-35 with a valid annual earnings observation (greater than $500). The regression samples for employed and occupation quality excludes enrolled workers but has no restriction on earnings. The full-time regression sample is restricted to those with a valid earnings observations. Enrolled is restricted to workers younger than 27.

Table 2: Characteristics of Selected Majors

Major:	β^{major}	SAT Math	SAT/ACT	LOGIC	Specificity
Economics	1.65	1.51	1.35	0.50	-0.51
Electrical Engineering	1.57	2.60	1.53	1.69	-0.17
Finance	1.49	0.70	0.81	0.25	0.01
Mechanical Engineering	1.37	1.91	1.61	1.98	-0.17
Chemistry	1.33	1.11	1.56	1.46	0.11
Civil Engineering	1.11	1.49	1.24	2.37	0.26
Nursing	0.94	-0.50	-1.74	1.81	4.66
Mathematics	0.90	1.45	1.05	0.97	-0.45
Political Science	0.86	0.00	1.04	0.59	-0.57
Business Mgmt/Admin	0.23	-0.30	-1.05	-0.46	-0.63
Communications	-0.18	-0.70	-0.15	-1.00	-0.63
Psychology	-0.68	-0.48	-0.43	-0.04	-0.61
Social Work and HR	-1.13	-1.35	-1.76	-0.10	-0.07
Family/Consumer Science	-1.26	-1.36	-1.01	-1.16	-0.37
Art History/Fine Arts	-1.40	0.28	0.66	-1.75	-0.36
Education (not secondary)	-1.49	-0.96	-0.93	-0.75	0.95
Philosophy and Religion	-2.41	0.72	1.10	0.01	-0.47

Notes: First 5 columns are given in standard deviations. See the text for details on each measure. For the full list of majors, see appendix table 5.

Table 3: Annual Earnings as a Function of Entry Conditions and Major Characteristics
Dependent variable: Log Annual Earnings

	All Workers				Full-Time Workers	
	(1)	(2)	(3)	(4)	(5)	(6)
Entry unemployment rate (U_c)	-0.0228*	-0.0226*			-0.0128	
	(0.0132)	(0.0131)			(0.0085)	
U_c*potexp	0.0071	0.0074	0.0071**	0.0071**	0.0040	0.0028
	(0.0045)	(0.0045)	(0.0028)	(0.0031)	(0.0026)	(0.0021)
U_c*potexp^2	-0.0006	-0.0007*	-0.0004*	-0.0004*	-0.0003	-0.0001
	(0.0004)	(0.0004)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
β^{major}	0.1738***					
	(0.0080)					
β^{major}*potexp	0.0039***	0.0035***	0.0026***	0.0026**	0.0027***	0.0023***
	(0.0012)	(0.0010)	(0.0009)	(0.0012)	(0.0009)	(0.0008)
β^{major}* U_c	0.0055	0.0127*	0.0134***	0.0134***	0.0058	0.0060**
	(0.0086)	(0.0071)	(0.0038)	(0.0052)	(0.0041)	(0.0030)
β^{major}* U_c*potexp	-0.0004	-0.0017*	-0.0016***	-0.0016**	-0.0005	-0.0005
	(0.0011)	(0.0009)	(0.0006)	(0.0007)	(0.0006)	(0.0004)
Major fixed effects		X	X	X	X	X
Grad year fixed effects			X	X		X
Cluster at grad year	X	X			X	
Cluster at grad year-major				X		
Observations	10,400	10,400	10,400	10,400	9,984	9,984
R-squared	0.527	0.574	0.585	0.585	0.673	0.680

Robust standard errors in parentheses, clustered as noted.

*** p<0.01, ** p<0.05, * p<0.1

Notes: Observations in these regressions are major-gradyear-potexp cells. We weight by the major's share of observations in the gradyear-potexp group. U_c is the national unemployment rate in the year the cohort graduated from college. Potexp is years since college graduation. β^{major} is the earnings return to the major, estimated on a sample of workers age 36-59 in our pooled, unweighted data. Survey dummies, year dummies, a quadratic in potential experience, gender, race, and region controls are also included. The sample is non-enrolled workers from age 22 to 35, with potential experience 1 to 13, with at least $500 in annual earnings in 2006 dollars. Only full-time workers are included in columns 5 and 6.

Table 4: Annual Earnings as a Function of Entry Conditions and Major Characteristics
Dependent variable: Log Annual Earnings

	SAT Math		LOGIC		Specificity	
	(1)	(2)	(3)	(4)	(5)	(6)
Entry unemployment rate (U_c)	-0.0201		-0.0174		-0.0203	
	(0.0140)		(0.0142)		(0.0143)	
U_c*potexp	0.0073	0.0082***	0.0067	0.0081***	0.0071	0.0092***
	(0.0048)	(0.0029)	(0.0048)	(0.0029)	(0.0050)	(0.0029)
U_c*potexp^2	-0.0007*	-0.0005**	-0.0006	-0.0005**	-0.0006	-0.0006**
	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0002)
Major variable (Z)	0.1110***		0.1238***		0.0479***	
	(0.0059)		(0.0094)		(0.0116)	
Z*potexp	0.0016	0.0019**	-0.0003	0.0000	-0.0069***	-0.0078***
	(0.0011)	(0.0009)	(0.0015)	(0.0010)	(0.0020)	(0.0010)
Z* U_c	0.0133**	0.0117***	0.0127**	0.0034	-0.0071	-0.0066*
	(0.0051)	(0.0037)	(0.0060)	(0.0036)	(0.0066)	(0.0038)
Z* U_c*potexp	-0.0006	-0.0009	-0.0013	-0.0007	-0.0001	0.0004
	(0.0008)	(0.0006)	(0.0009)	(0.0006)	(0.0008)	(0.0006)
Major fixed effects		X		X		X
Grad year fixed effects		X		X		X
Cluster at grad year	X		X		X	
Observations	10,042	10,042	10,121	10,121	10,121	10,121
R-squared	0.430	0.588	0.430	0.586	0.322	0.585

Robust standard errors in parentheses, clustered as noted.
*** p<0.01, ** p<0.05, * p<0.1

Notes: Observations in these regressions are major-gradyear-potexp cells. We weight by the major's share of observations in the gradyear-potexp group. U_c is the national unemployment rate in the year the cohort graduated from college. Potexp is years since college graduation. SAT Math is the average score in the major in B&B data. LOGIC is the average of the O*Net factor in the major. Specificity is a Herfindahl index of occupations for each major. Survey dummies, year dummies, a quadratic in potential experience, gender, race, and region controls are also included. The sample is non-enrolled workers from age 22 to 35, with potential experience 1 to 13, with at least $500 in annual earnings in 2006 dollars.

Table 5: Employment, Full-time Employment, and Pay Rates as a Function of Entry Conditions and Major Characteristics

	Dependent Variable:					
	Employed		Full-time		Log pay rate	
	(1)	(2)	(3)	(4)	(5)	(6)
Entry unemployment rate (U_c)	0.0052		-0.0279***		-0.0328***	
	(0.0042)		(0.0065)		(0.0091)	
U_c*potexp	-0.0005	0.0005	0.0129***	0.0155***	0.0092***	0.0116***
	(0.0016)	(0.0011)	(0.0026)	(0.0019)	(0.0033)	(0.0027)
U_c*potexp^2	-0.0000	0.0000	-0.0010***	-0.0012***	-0.0007***	-0.0007***
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0003)	(0.0002)
β^{major}*potexp	0.0010**	0.0008**	-0.0012**	-0.0014***	0.0027*	0.0016
	(0.0004)	(0.0003)	(0.0005)	(0.0005)	(0.0015)	(0.0011)
β^{major}* U_c	0.0014	0.0016	0.0039	0.0030	0.0034	0.0028
	(0.0020)	(0.0016)	(0.0030)	(0.0027)	(0.0062)	(0.0036)
β^{major}* U_c*potexp	-0.0003	-0.0003	-0.0002	-0.0001	0.0002	0.0004
	(0.0003)	(0.0002)	(0.0004)	(0.0004)	(0.0008)	(0.0005)
Major fixed effects	X	X	X	X	X	X
Grad year fixed effects		X		X		X
Cluster at grad year	X		X		X	
Observations	11,018	11,018	10,400	10,400	10,369	10,369
R-squared	0.309	0.329	0.285	0.292	0.990	0.990

Robust standard errors in parentheses, clustered as noted.

*** p<0.01, ** p<0.05, * p<0.1

Note: Observations in these regressions are major-gradyear-potexp cells. Dependent variable is employment in columns 1 and 2, full-time in columns 3 and 4, and log pay rate in columns 5 and 6. We weight by the major's share of observations in the gradyear-potexp group. β^{major} is the earnings return to the major, estimated on a sample of workers age 36-59 in our pooled, unweighted data. Survey dummies, year dummies, a quadratic in potential experience, gender, race, and region controls are also included. Survey dummies, year dummies, gender, race, and region are also included. The employment sample is non-enrolled workers from age 22 to 35, with potential experience 0 to 13; the sample for full-time is the same as the earnings sample, see table 3; the sample for log pay rate are non-enrolled workers with potexp between 1 and 13 with a valid pay rate observation.

Table 6: Understanding Mechanisms for the Effects of Entry Conditions across Major: Occupation Quality and Specificity

	Dependent Variable:			
	Occupation Quality		Log Annual Earnings	
	(1)	(2)	(3)	(4)
Entry unemployment rate (U_c)	-0.0003			
	(0.0024)			
U_c*potexp	-0.0005	-0.0008	0.0071**	0.0077***
	(0.0011)	(0.0011)	(0.0028)	(0.0029)
U_c*potexp^2	0.0000	0.0001	-0.0004*	-0.0005**
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
β^{major}*potexp	0.0001	0.0001	0.0026***	0.0026***
	(0.0003)	(0.0004)	(0.0009)	(0.0009)
β^{major}* U_c	-0.0019	-0.0017	0.0134***	0.0134***
	(0.0017)	(0.0016)	(0.0038)	(0.0037)
β^{major}* U_c*potexp	0.0002	0.0002	-0.0016***	-0.0016***
	(0.0002)	(0.0002)	(0.0006)	(0.0006)
Specificity*potexp				-0.0075***
				(0.0010)
Specificity*U_c				-0.0076**
				(0.0036)
Specificity*U_c*potexp				0.0005
				(0.0006)
Major FE	X	X	X	X
Grad year FE		X		X
Cluster at grad year	X		X	
Observations	10,725	10,725	10,400	10,400
R-squared	0.650	0.652	0.585	0.585

Robust standard errors in parentheses, clustered as noted.
*** p<0.01, ** p<0.05, * p<0.1

Notes: Observations in these regressions are major-gradyear-potexp cells. The depdendent variable in columns 1 and 2 is the occupational fixed effect estimated from a log earnings regression in the ACS. The dependent variable in columns 3 and 4 is log annual earnings. We weight by the major's share of observations in the gradyear-potexp group. U_c is the national unemployment rate in the year the cohort graduated from college. Potexp is years since college graduation. β^{major} is the earnings return to the major, estimated on a sample of workers age 36-59 in our pooled, unweighted data. Specificity is a Herfindahl index of occupations for each major. Survey dummies, year dummies, a quadratic in potential experience, gender, race, and region controls are also included. The sample is non-enrolled workers from age 22 to 35, with potential experience 1 to 13, and the log earnings regression is further restricted to those with at least $500 in annual earnings in 2006 dollars.

Table 7: Understanding Mechanisms for the Effects of Entry Conditions across Major: Major-Specific Cyclicality

	Dependent Variable:			
	U_c^{major}		Log annual earnings	
	(1)	(2)	(3)	(4)
Entry unemployment rate (U_c)	0.4448***	0.5698***		
	(0.0129)	(0.0158)		
U_c*potexp			0.0077***	0.0081***
			(0.0029)	(0.0029)
U_c*potexp^2			-0.0005**	-0.0005**
			(0.0002)	(0.0002)
β^{major}	-0.1013***	-0.1013***		
	(0.019)	(0.016)		
β^{major}*potexp			0.0028***	0.0028***
			(0.0009)	(0.0009)
β^{major}* U_c	-0.0275**	-0.0275***	0.0134***	0.0127***
	(0.0123)	(0.0103)	(0.0038)	(0.0038)
β^{major}* U_c*potexp			-0.0015***	-0.0015***
			(0.0006)	(0.0006)
U_c^{major}				0.0338***
				(0.0109)
U_c^{major}*potexp				-0.0007
				(0.0015)
Major FE			X	X
Grad year FE			X	X
Cubic time trend		X		
Observations	2,091	2,091	10,121	10,121
R-squared	0.369	0.565	0.591	0.592

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Note: In columns 1 and 2, the dependent variable is the major-specific unemployment rate in the graduation year, U_c^{major}, created using a major-to-occupation mapping and occupation-specific unemployment rates. An observation is a major-year. No additional controls are included other than the cubic time trend in column 2. The dependent variable in columns 3 and 4 is log annual earnings or salary. An observation is a major-gradyear-potexp cell. We weight by the major's share of observations in the gradyear-potexp group. These columns include survey dummies, year dummies, gender, race, and region. U_c is the national unemployment rate in the year the cohort graduated from college. Potexp is years since college graduation. β^{major} is the earnings return to the major, estimated on a sample of workers age 36-59 in our pooled, unweighted data. The earnnings sample is non-enrolled workers from age 22 to 35, with potential experience 1 to 13, with at least $500 in annual earnings in 2006 dollars.

Table 8: Enrollment and Educational Attainment as a Function of Entry Econiditons and Major Characteristic

	Dependent Variable			
	Enrollment		Highest grade completed	
	(1)	(2)	(3)	(4)
Entry unemployment rate (U_c)	-0.0174*		-0.0091	
	(0.0095)		(0.0150)	
U_c*potexp	0.0070***	0.0115***		
	(0.0024)	(0.0033)		
U_c*potexp^2	-0.0005***	-0.0008***		
	(0.0002)	(0.0002)		
β^{major}*potexp	-0.0022***	-0.0019***		
	(0.0008)	(0.0006)		
β^{major}* U_c	0.0010	-0.0008	-0.0222**	-0.0219***
	(0.0038)	(0.0041)	(0.0095)	(0.0060)
β^{major}* U_c*potexp	0.0004	0.0005		
	(0.0003)	(0.0005)		
Major FE	X	X	X	X
Grad year FE		X		X
Clustered at grad year	X		X	
Observations	8,426	8,426	7,038	7,038
R-squared	0.475	0.485	0.463	0.499

Robust standard errors in parentheses, clulstered as noted.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Observations in these regressions are major-gradyear-potexp cells. We weight by the major's share of observations in the gradyear-potexp group. U_c is the national unemployment rate in the year the cohort graduated from college. Potexp is years since college graduation. β^{major} is the earnings return to the major, estimated on a sample of workers age 36-59 in our pooled, unweighted data. Survey dummies, year dummies, a quadratic in potential experience (in columns 1 and 2 only), gender, race, and region controls are also included. The sample in columns 1 and 2 is workers 22 to 26. The sample in columns 3 and 4 is workers 22 to 35.

Table 9: Annual Earnings as a Function of Entry Conditions and Major, by Gender

	Men		Women	
	(1)	(2)	(3)	(4)
Entry unemployment rate (U_c)	-0.0277**		-0.0167	
	(0.0131)		(0.0161)	
U_c*potexp	0.0069	0.0065*	0.0052	0.0053
	(0.0042)	(0.0036)	(0.0063)	(0.0039)
U_c*potexp^2	-0.0005	-0.0004	-0.0005	-0.0002
	(0.0003)	(0.0003)	(0.0005)	(0.0003)
β^{major}*potexp	0.0013	0.0007	0.0054***	0.0039***
	(0.0012)	(0.0011)	(0.0014)	(0.0012)
β^{major}* U_c	-0.0026	-0.0020	0.0164**	0.0172***
	(0.0074)	(0.0048)	(0.0075)	(0.0050)
β^{major}* U_c*potexp	0.0005	0.0005	-0.0026**	-0.0024***
	(0.0009)	(0.0007)	(0.0010)	(0.0008)
Major FE	X	X	X	X
Grad year FE		X		X
Clustered at grad year	X		X	
Observations	8,952	8,952	8,875	8,875
R-squared	0.636	0.642	0.441	0.457

Robust standard errors in parentheses, clulstered as noted.
*** p<0.01, ** p<0.05, * p<0.1

Notes: Observations in these regressions are major-gradyear-potexp cells. We weight by the major's share of observations in the gradyear-potexp group. Uc is the national unemployment rate in the year the cohort graduated from college. Potexp is years since college graduation. βmajor is the earnings return to the major, estimated on a sample of workers age 36-59 in our pooled, unweighted data. Survey dummies, year dummies, a quadratic in potential experience, gender, race, and region controls are also included. The sample is non-enrolled workers from age 22 to 35, with potential experience 1 to 13, with at least $500 in annual earnings in 2006 dollars. Only full-time workers are included in columns 5 and 6.

Table 10: Quantile Regressions on Earnings
Dependent Variable: Log Annual Earnings

	90th pctile (1)	50th pctile (2)	10th pctile (3)
Entry unemployment rate (U_c)	-0.0045*	-0.0159***	-0.0390***
	(0.0025)	(0.0018)	(0.0071)
U_c*potexp	0.0047***	0.0051***	0.0103***
	(0.0010)	(0.0007)	(0.0028)
U_c*potexp^2	-0.0004***	-0.0004***	-0.0008***
	(0.0001)	(0.0001)	(0.0002)
β^{major}	0.1459***	0.1542***	0.1672***
	(0.0031)	(0.0022)	(0.0087)
β^{major}*potexp	0.0035***	0.0027***	0.0056***
	(0.0005)	(0.0003)	(0.0013)
β^{major}* U_c	-0.0063***	0.0083***	0.0223***
	(0.0018)	(0.0013)	(0.0050)
β^{major}* U_c*potexp	0.0013***	-0.0007***	-0.0016*
	(0.0003)	(0.0002)	(0.0008)
Constant	10.6823***	10.1651***	9.1863***
	(0.0310)	(0.0219)	(0.0865)
Observations	398,827	398,827	398,827

Robust standard errors in parentheses, clulstered as noted.
*** p<0.01, ** p<0.05, * p<0.1

Notes: Observations in these regressions are individual earnings observations. We weight each grad year-potexp cell equally. U_c is the national unemployment rate in the year the cohort graduated from college. Potexp is years since college graduation. β^{major} is the earnings return to the major, estimated on a sample of workers age 36-59 in our pooled, unweighted data. Survey dummies, year dummies, a quadratic in potential experience, gender, race, and region controls are also included. The sample is non-enrolled workers from age 22 to 35, with potential experience 1 to 13, with at least $500 in annual earnings in 2006 dollars.

Table 11: Earnings and Pay Rates Effects across Recessions: Pre-1998 vs. Post-1998

	Dependent Variable			
	Log Annual Earnings		Log Pay Rate	
	(1)	(2)	(3)	(4)
Entry unemployment rate (U_c)	0.0015		-0.0241**	
	(0.0125)		(0.0109)	
U_c*$After$	-0.0816***		-0.0306	
	(0.0201)		(0.0224)	
U_c*potexp	0.0031	0.0033	0.0064	0.0032
	(0.0052)	(0.0039)	(0.0042)	(0.0034)
U_c*potexp*$After$	0.0263***	0.0218**	0.0110	-0.0036
	(0.0079)	(0.0098)	(0.0072)	(0.0113)
U_c*potexp^2	-0.0004	-0.0002	-0.0004	0.0000
	(0.0005)	(0.0003)	(0.0004)	(0.0003)
U_c*potexp^2*$After$	-0.0020***	-0.0020**	-0.0008	-0.0004
	(0.0007)	(0.0008)	(0.0006)	(0.0010)
β^{major}*$After$	0.0560***	0.0595***	0.0216	0.0236
	(0.0161)	(0.0156)	(0.0241)	(0.0216)
β^{major}*U_c	0.0333***	0.0333***	0.0096	0.0090
	(0.0073)	(0.0064)	(0.0096)	(0.0063)
β^{major}*U_c*$After$	-0.0342***	-0.0354***	-0.0155	-0.0157*
	(0.0089)	(0.0084)	(0.0121)	(0.0082)
β^{major}*U_c*potexp	-0.0043***	-0.0042***	-0.0012	-0.0010
	(0.0010)	(0.0009)	(0.0012)	(0.0009)
β^{major}*U_c*potexp*$After$	0.0033***	0.0033***	0.0007	0.0007
	(0.0011)	(0.0012)	(0.0014)	(0.0013)
Major FE	X	X	X	X
Grad year FE		X		X
Cluster at grad year	X		X	
Observations	10,400	10,400	10,369	10,369
R-squared	0.580	0.586	0.990	0.990

Robust standard errors in parentheses, clulstered as noted.

*** p<0.01, ** p<0.05, * p<0.1

Notes: Observations in these regressions are major-gradyear-potexp cells. We weight by the major's share of observations in the gradyear-potexp group. U_c is the national unemployment rate in the year the cohort graduated from college. Potexp is years since college graduation. β^{major} is the earnings return to the major, estimated on a sample of workers age 36-59 in our pooled, unweighted data. Survey dummies, year dummies, a quadratic in potential experience, gender, race, and region controls are also included. The sample is non-enrolled workers from age 22 to 35, with potential experience 1 to 13, with at least \$500 in annual earnings in 2006 dollars. The dummy variable *After* is equal to 1 if the worker graduated in 1998 or later.

Appendix Table 1
Data Sources (Earnings Sample)

Data source	Grad years	Earnings years	Earnings observations
NLSY79	1979-1988	1980-1993, 1995, 1997	9,134
NLSY97	2001-2008	2002-2009	3,621
NLS72	1976-1978	1977-1986	6,157
B&B 93/03	1993	1994, 1997, 2003	14,357
B&B 08/09	2008	2009	6,579
NSCG 1993	1980-1990	1993	24,832
NSCG 2003	1990-2000	2003	11,575
ACS 09-11	1996-2010	2009-2011	281,730
SIPP	1976-2008	1984-2011	46,628

Appendix Table 2
Sample Coverage: Graduation Unemployment Rates and Potential Experience

	Potential experience					
U_c	1-2	3-4	5-7	8-10	11-13	Total
<5%	7,404	29,765	12,944	51,876	59,358	161,347
5-6%	19,658	19,824	55,850	21,449	6,635	123,416
6-7%	6,621	6,643	21,432	19,467	3,007	57,170
7-8%	4,244	3,705	8,199	10,822	8,492	35,462
8-9%	0	0	0	0	0	0
>9%	16,999	837	1353	4,404	3,527	27,120
Total	54,926	60,774	99,778	108,018	81,019	404,515

Appendix Table 3
Summary Statistics for Earnings Sample (Unweighted)

Variable	n	Mean	St Dev	Min	Max
Male	403,963	0.46	0.50	0	1
Black	403,963	0.06	0.24	0	1
Hispanic	403,963	0.07	0.25	0	1
Potential experience	403,963	7.00	3.53	1	13
Graduation year	403,963	1999.13	7.87	1976	2010
Graduation unemployment rate (%)	403,963	5.64	1.40	4.0	9.7
Year	403,963	2006.12	7.38	1977	2011
Current unemployment rate (%)	403,963	8.45	1.48	4.2	9.7
Annual earnings (2006 $)	403,963	48,440	37,375	501	400,000*
Log annual earnings	403,963	10.52	0.81	6.22	12.90
Employed	403,963	0.96	0.19	0	1
Highest grade completed	403,963	16.62	1.08	16	20
Summary Statistics for Relevant Samples (Unweighted)					
Employed	461,005	0.88	0.32	0	1
Full-time	403,963	0.89	0.31	0	1
Enrolled	135,785	0.27	0.44	0	1
Occupational earnings	461,005	-0.79	0.33	-1.61	0.04
Highest grade completed	542,509	16.59	1.06	16	20

Appendix Table 4a: B&B to Early SIPP Major Crosswalk

Early SIPP Major	B&B Major	B&B Share (Men)	B&B Share (Women)
Agriculture/Forestry	Agriculture/Ag Science	1.00	1.00
Biology	Biological Sciences	1.00	1.00
Business/Mgmt	Finance	0.16	0.10
Business/Mgmt	Marketing	0.21	0.25
Business/Mgmt	Business Mgmt/Admin	0.14	0.20
Business/Mgmt	Accounting	0.49	0.45
Economics	Economics	1.00	1.00
Education	Secondary Education	0.08	0.03
Education	Other Education and Library Sci	0.92	0.97
Engineering/Computers	All Other Engineering	0.21	0.23
Engineering/Computers	Chemical Engineering	0.04	0.08
Engineering/Computers	Civil Engineering	0.07	0.08
Engineering/Computers	Computer Programming	0.05	0.09
Engineering/Computers	Computer/Info Tech	0.24	0.28
Engineering/Computers	Electrical Engineering	0.14	0.10
Engineering/Computers	Engineering Tech	0.06	0.05
Engineering/Computers	Mechanical Engineering	0.14	0.08
Engineering/Computers	Precision Production/Industrial Arts	0.04	0.02
English/Journalism	Communications	0.49	0.44
English/Journalism	Journalism	0.40	0.45
English/Journalism	Letters: Lit, Writing, Other	0.10	0.10
Home Economics	Family and Consumer Science	1.00	1.00
Law	Public Administration and Law	1.00	1.00
Liberal Arts/Humanities	Foreign Language	1.00	1.00
Math/Statistics	Mathematics	1.00	1.00
Medicine/Dentistry		--	--
Nursing/Pharm/Health	Misc. Business and Med. Support	0.54	0.24
Nursing/Pharm/Health	Fitness and Nutrition	0.19	0.10
Nursing/Pharm/Health	Other Med/Health Services	0.17	0.26
Nursing/Pharm/Health	Medical Tech	0.02	0.02
Nursing/Pharm/Health	Public Health (Physical and Mental)	0.02	0.02
Nursing/Pharm/Health	Nursing	0.07	0.35
Other	Leisure Studies and Basic Skills	0.11	0.10
Other	Architecture	0.19	0.09
Other	Commercial Art and Design	0.15	0.21
Other	Art History and Fine Arts	0.21	0.27
Other	Film and Other Arts	0.13	0.14
Other	Music and Speech/Drama	0.22	0.19
Physical/Earth Science	Multidisciplinary or General Science	0.16	0.29
Physical/Earth Science	Physics	0.23	0.09
Physical/Earth Science	Chemistry	0.34	0.40
Physical/Earth Science	Earth and Other Physical Sci	0.27	0.22
Police Science	Protective Services	1.00	1.00
Psychology	Psychology	0.85	0.77
Psychology	Social Work and Human Resources	0.15	0.23
Religion/Theology	Philosophy and Religion	1.00	1.00
Social Sciences	Other Social Science	0.28	0.42
Social Sciences	Area, Ethnic, and Civic Studies	0.03	0.06
Social Sciences	Political Science	0.29	0.23
Social Sciences	History	0.26	0.16
Social Sciences	International Relations	0.05	0.07
Social Sciences	Environmental Studies	0.09	0.06
Vocational Studies	--	--	--

Appendix Table 4b: B&B to Late SIPP Major Crosswalk

Late SIPP Major	B&B Major	B&B Share (Men)	B&B Share (Women)
Agriculture/Forestry	Agriculture and Agr. Science	1.00	1.00
Art/Architecture	Precision Production & Industrial Arts	0.16	0.02
Art/Architecture	Architecture	0.17	0.09
Art/Architecture	Commercial Art and Design	0.14	0.23
Art/Architecture	Art History and Fine Arts	0.19	0.30
Art/Architecture	Film and Other Arts	0.12	0.15
Art/Architecture	Music and Speech/Drama	0.21	0.21
Business/Mgmt	Economics	0.13	0.08
Business/Mgmt	Finance	0.14	0.09
Business/Mgmt	Marketing	0.12	0.19
Business/Mgmt	Business Management and Administration	0.43	0.42
Business/Mgmt	Accounting	0.18	0.23
Communications	Communications	0.83	0.81
Communications	Journalism	0.17	0.19
Computer/Info Tech	Computer and Info Tech	0.83	0.75
Computer/Info Tech	Computer Programming	0.17	0.25
Education	Secondary Education	0.08	0.03
Education	Library Science and Education (Other)	0.88	0.87
Education	Family and Consumer Science	0.04	0.10
Engineering	All Other Engineering	0.32	0.38
Engineering	Mechanical Engineering	0.21	0.12
Engineering	Electrical Engineering	0.21	0.16
Engineering	Civil Engineering	0.11	0.13
Engineering	Chemical Engineering	0.06	0.12
Engineering	Engineering Tech	0.09	0.08
English/Literature	Letters: Lit, Writing, Other	1.00	1.00
Foreign Languages	Foreign Language	1.00	1.00
Health Sciences	Misc. Business and Med. Support	0.54	0.24
Health Sciences	Fitness and Nutrition	0.19	0.10
Health Sciences	Other Med/Health Services	0.17	0.26
Health Sciences	Medical Tech	0.02	0.02
Health Sciences	Public Health (Physical and Mental)	0.02	0.02
Health Sciences	Nursing	0.07	0.35
Lib Arts/Humanities	--	--	--
Math/Statistics	Mathematics	1.00	1.00
Nature Sciences	Multidisciplinary or General Science	0.07	0.08
Nature Sciences	Physics	0.09	0.02
Nature Sciences	Chemistry	0.14	0.11
Nature Sciences	Earth and Other Physical Sci	0.11	0.06
Nature Sciences	Biological Sciences	0.60	0.73
Other	Leisure Studies and Basic Skills	1.00	1.00
Philogophy/Religion	Philosophy and Religion	1.00	1.00
Pre-Professional	Public Administration and Law	1.00	1.00
Psychology	Psychology	0.85	0.77
Psychology	Social Work and Human Resources	0.15	0.23
Social Sciences	Other Social Science	0.23	0.36
Social Sciences	Area, Ethnic, and Civ. Studies	0.02	0.05
Social Sciences	Political Science	0.24	0.19
Social Sciences	Protective Services	0.19	0.14
Social Sciences	History	0.21	0.14
Social Sciences	International Relations	0.04	0.06
Social Sciences	Environmental Studies	0.08	0.05

Appendix Table 5: Characteristics of B&B Major Categories

Major	β^{major}	SAT Math	SAT/ACT	LOGIC	Specificity
Chemical Engineering	1.95	*	2.17	1.97	-0.28
Economics	1.65	1.51	1.35	0.50	-0.51
Electrical Engineering	1.57	2.60	1.53	1.70	-0.08
Finance	1.49	0.70	0.81	0.25	0.01
Mechanical Engineering	1.37	1.91	1.61	1.98	-0.17
Chemistry	1.33	1.11	1.56	1.46	0.11
Computer Programming	1.29	*	-0.91	0.04	0.53
All Other Engineering	1.13	1.76	1.29	1.41	-0.34
Biological Sciences	1.12	1.05	1.32	1.31	-0.59
Computer and Info Tech	1.12	0.81	0.28	1.18	0.83
Civil Engineering	1.11	1.49	1.24	2.37	0.26
Accounting	1.02	*	-0.05	0.84	2.06
Nursing	0.94	-0.50	-1.75	1.81	4.66
Mathematics	0.90	1.45	1.05	0.97	-0.45
Political Science	0.86	0.00	1.04	0.59	-0.57
Physics	0.79	*	2.58	1.76	0.38
International Relations	0.76	0.47	0.95	0.21	-0.54
Marketing	0.63	-0.31	-0.95		-0.47
Other Med/Health Services	0.60	-0.50	-0.42	0.22	-0.54
Misc. Business and Med. Support	0.58	*	-0.94	-0.30	0.21
Precision Production/Industrial Arts	0.47	*	-0.43	0.43	2.01
Medical Tech	0.46	*	-1.69	-0.77	1.30
Business Mgmt and Administration	0.23	-0.30	-1.05	-0.46	-0.63
Earth and Other Physical Sciences	0.20	*	0.93	0.86	-0.50
Area, Ethnic, and Civic Studies	0.12	0.54	1.95	-0.12	-0.39
Engineering Tech	0.08	-0.30	-0.56	0.11	-0.51
Public Administration and Law	0.06	*	-1.60	-0.14	-0.19
Multidisciplinary/General Science	0.03	*	-0.18	0.20	-0.47
Journalism	0.01	*	0.17	-0.70	-0.53
Architecture	0.01	*	1.03	1.51	-0.09
History	-0.14	0.19	0.98	-0.12	-0.57
Communications	-0.18	-0.70	-0.15	-1.00	-0.63
Public Health (Physical and Mental)	-0.43	*	1.02	0.24	-0.03
Protective Services	-0.47	*	-1.59	-0.78	-0.41
Letters: Literature/Writing	-0.59	0.28	0.92	-0.68	-0.56
Foreign Language	-0.61	0.41	0.59	-0.42	-0.56
Environmental Studies	-0.67	0.25	-0.04	-0.11	-0.46
Psychology	-0.68	-0.48	-0.43	-0.04	-0.61
Other Social Science	-0.72	-0.69	-0.57	-0.54	-0.65
Leisure Studies and Basic Skills	-0.75	-1.23	-1.58	-1.73	-0.32
Fitness and Nutrition	-1.00	-0.99	-0.93	-1.04	-0.43
Commercial Art and Design	-1.04	-0.45	-0.19	-1.77	0.90
Agriculture and Agr. Science	-1.09	0.10	0.60	-1.04	-0.58
Social Work and Human Resources	-1.13	-1.35	-1.76	-0.10	-0.07
Family and Consumer Science	-1.26	-1.36	-1.01	-1.16	-0.37
Art History and Fine Arts	-1.40	0.28	0.66	-1.75	-0.36
Secondary Education	-1.41	*	0.04	-0.46	1.66
Other Education and Library Sci	-1.49	-0.96	-0.93	-0.75	0.95
Film and Other Arts	-1.70	-0.11	0.48	-2.13	-0.52
Music and Speech/Drama	-1.83	-0.52	0.10	-1.84	-0.55
Philosophy and Religion	-2.41	0.72	1.10	0.01	-0.47

*We cannot report these values for confidentiality reasons. We do, however, use them in our regressions. See data appendix for details of each variable

Appendix Table 6: Annual Earnings -- Unweighted
Dependent variable: Log Annual Earnings

	(1)	(2)	(3)	(4)
Entry unemployment rate (U_c)	-0.0410***	-0.0408***		
	(0.0068)	(0.0047)		
U_c*potexp	0.0100***	0.0099***	0.0069***	0.0069***
	(0.0024)	(0.0020)	(0.0024)	(0.0024)
U_c*potexp^2	-0.0008***	-0.0007***	-0.0002	-0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
β^{major}	0.1648***			
	(0.0118)			
β^{major}*potexp	0.0008	0.0009	0.0005	0.0005
	(0.0014)	(0.0009)	(0.0009)	(0.0009)
β^{major}* U_c	0.0022	0.0028	0.0030	0.0030
	(0.0058)	(0.0035)	(0.0035)	(0.0035)
β^{major}* U_c*potexp	-0.0008	-0.0012***	-0.0013***	-0.0013***
	(0.0006)	(0.0004)	(0.0004)	(0.0004)
Major fixed effects		X	X	X
Grad year fixed effects			X	X
Cluster at grad year	X	X		
Cluster at grad year-major				X
Observations	403,226	403,226	403,226	403,226
R^2	0.186	0.193	0.194	0.194

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Observations in these regressions are individual earnings observations. U_c is the national unemployment rate in the year the cohort graduated from college. Potexp is years since college graduation. βmajor is the earnings return to the major, estimated on a sample of workers age 36-59 in our pooled, unweighted data. Survey dummies, year dummies, a quadratic in potential experience, gender, race, and region controls are also included. The sample is non-enrolled workers from age 22 to 35, with potential experience 1 to 13, with at least $500 in annual earnings in 2006 dollars.

Appendix Table 7: Earnings Using Regional Unemployment Rates
Dependent variable: Log Annual Earnings

	(1)	(2)	(3)	(4)
Entry unemployment rate (U_c)	-0.0197***	-0.0193***	-0.0487***	-0.0487***
	(0.0066)	(0.0062)	(0.0127)	(0.0157)
U_c*potexp	0.0051*	0.0058**	0.0062**	0.0062**
	(0.0028)	(0.0028)	(0.0028)	(0.0029)
U_c*potexp^2	-0.0004*	-0.0005**	-0.0004*	-0.0004*
	(0.0003)	(0.0002)	(0.0002)	(0.0002)
β^{major}	0.1669***			
	(0.0077)			
β^{major}*potexp	0.0045***	0.0037***	0.0031***	0.0031***
	(0.0011)	(0.0010)	(0.0010)	(0.0010)
β^{major}* U_c	0.0051	0.0112**	0.0122***	0.0122***
	(0.0053)	(0.0044)	(0.0040)	(0.0045)
β^{major}* U_c*potexp	-0.0009	-0.0019***	-0.0019***	-0.0019***
	(0.0007)	(0.0006)	(0.0006)	(0.0007)
Major fixed effects		X	X	X
Grad year fixed effects			X	X
Cluster at grad year	X	X		
Cluster at grad year-major				X
Observations	10,400	10,400	10,400	10,400
R-squared	0.480	0.530	0.539	0.539

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Observations in these regressions are major-gradyear-potexp cells. We weight by the major's share of observations in the gradyear-potexp group. U_c is the regional (4 Census regions) unemployment rate in the year the cohort graduated from college. Potexp is years since college graduation. βmajor is the earnings return to the major, estimated on a sample of workers age 36-59 in our pooled, unweighted data. Survey dummies, year dummies, a quadratic in potential experience, gender, race, and region controls are also included. The sample is non-enrolled workers from age 22 to 35, with potential experience 1 to 13, with at least $500 in annual earnings in 2006 dollars.