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Caught in the Cycle: Economic Conditions at Enrollment and Labor Market Outcomes of College Graduates*

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Abstract

We find robust evidence that cohorts of graduates who enter college during worse economic times earn higher average wages than those who enter during better times. This difference is not explained by differences in economic conditions at the time of college graduation, changes in field of study composition, or changes in selection into occupations or industries. Cohorts who start college in bad times are not more positively selected based on their high-school outcomes, but they graduate with higher college grades, and earn higher wages conditional on their grades. Our results suggest that these cohorts exert more effort during their studies.

Keywords: Business Cycle, Higher Education, Cohort Effects

JEL Classification: I23, J24, J31, E32

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1 Introduction

Do business cycle fluctuations have long-lasting impacts on individual outcomes? The answer to this question is crucial for our understanding of the welfare consequences of recessions. Most of the literature on this topic has focused on the long-term earnings losses induced by recessions, due to job separations or decreased job finding probabilities.[1] Recessions, however, also impact long-term individual outcomes through a separate and equally crucial channel, namely by influencing investment in human capital. Several contributions to the literature have shown that enrollment in higher education tends to increase during economic downturns.[2] In spite of this well-documented link, little is known about how cohorts who enroll into college during downturns end up performing once they enter the labor market. Analyzing how these cohorts perform is essential in order to understand the long-term impacts of recessions that operate via changes in human capital investment decisions.

There are strong reasons to expect that the labor market outcomes of cohorts who enroll during adverse economic times will differ from those who enroll during periods of low unemployment. The increase in college enrollment observed during recessions is likely associated with a change in the composition of skills among the cohort of students. At the same time, the resources available per student may vary over the business cycle.[3] Finally, the recession may affect students' career choices, or induce changes in the time and effort that students allocate towards their studies.

This paper analyzes the link between economic conditions at the time of college enrollment and future labor market outcomes using data from fifty-one cohorts of male college graduates in the United Kingdom. Our key finding is that cohorts that select into university during worse economic times have systematically better average labor market outcomes than those who select during better times. This difference is not explained by differences in the economic conditions at the time of college graduation, by changes in the composition of the cohorts in terms of field of study, or by changes in

[1] Davis and von Wachter (2011), for example, show that workers who exogenously lose their job during times of high unemployment experience substantially larger permanent earnings losses than those who experience a similar shock when unemployment rates are lower. A number of papers show that entering the labor market during a recession has long-lasting negative effects on individuals' career outcomes (Aslund and Rooth, 2007; Kahn, 2010; Oreopoulos et al., 2012; Altonji et al., 2016b; Liu et al., 2016; Schwandt and von Wachter, 2019).

[2] See, among others, Betts and McFarland (1995); Dellas and Sakellaris (2003); Clark (2011); Méndez and Sepúlveda (2012); Johnson (2013); Barr and Turner (2013, 2015); Sievertsen (2016); Atkin (2016) and Charles et al. (2018).

[3] Kane et al. (2005) show that, due to balanced budget requirements, state appropriations for higher education in the U.S. tend to fall during economic downturns. Note that even if funding remained constant, the increase in enrollment during downturns would lead to a decline in resources per student. Bound et al. (2010) show that resources per student outside of the most selective universities have declined over time as enrollment cohorts have become larger.

selection into occupations or industries. Using information on nationally comparable measures of academic achievement at both the high school and the college level, we show that the wage differentials cannot be explained by changes in the composition of students at the point of college entry. Rather, the results point towards an increase in the effort provided by students during their college years.

Our analysis relies on data from the UK Quarterly Labour Force Survey from 1998 to 2016. By exploiting information on the timing of graduation, we construct a long series of cohorts based on their year of college enrollment, ranging from 1960 to 2010.[4] Our empirical approach compares wage outcomes across cohorts of college graduates who enroll at different points in the business cycle. Relying on the rich cross-sectional and time dimensions of our data, and the fact that an individual's enrollment cohort is not a perfect function of their age and the calendar year when their wages are observed (because individuals may enroll into college at different ages), our identification approach allows for fully flexible time and age effects, and identifies the effect of business cycle conditions at entry based on the deviations of cohort quality from a linear long-run trend. Business cycle conditions are proxied by the average national unemployment rate in the three years leading up to the year of enrollment.

We find that, conditional on age effects, time effects, and the long-run trend in cohort quality, a 3 percentage point increase in the unemployment rate at the time of enrollment (approximately one standard deviation in the sample), increases average cohort wages by around 3.6%. The positive effect on wages is not driven by differential selection into employment and is experienced throughout the cohort's entire wage distribution, with particularly pronounced effects on the upper half.

We consider three mechanisms that could potentially explain our results: (i) the correlation between unemployment at entry and unemployment at exit from college; (ii) the impact of the business cycle on students' major choices; and (iii) changes in selection into different industries or occupations across cohorts entering university at different phases of the business cycle. We do not find any evidence supporting any of these three channels in our data. Unemployment rates at enrollment and graduation are positively correlated over our estimation period, implying that individuals who enroll during bad times tend to, on average, also enter the labor market during relatively bad times. Adding controls for the economic conditions at the time of graduation to our wage equations therefore does not alter our results. In terms of changes in major choices over the business cycle, we do not observe a large shift towards higher paying majors among students who enroll during periods of poor macroeconomic conditions.

[4] Throughout the paper we follow the convention in the literature to refer to university as "college". The group that would normally be referred to as college graduates in the UK (those who completed A-levels) are referred to in this paper as high-school graduates. More details about the UK education system are provided in Section 2.1.

This contrasts with the evidence for US undergraduate students in Blom et al. (2015) and likely reflects institutional features in the UK context that limit the ability of students to switch undergraduate majors. Lastly, we find that most of the wage differences occur within occupation-field-year or industry-field-year cells, and hence cannot be explained by differential selection into occupations or industries.

Our results provide strong evidence that the ex-post quality of cohorts who enroll during bad times is higher than that of cohorts who enroll during good times. This implies that there is either better ex-ante selection at the time of college entry, or there are changes in ability (i.e. differential human capital accumulation) occurring during the cohort's college years. In order to distinguish between these two potential explanations, we leverage information on academic achievements at both the high-school and the university level.

Consistent with the intuition that marginal students who decide to enroll during bad times would tend to be drawn from the lower end of the ability distribution of potential college-goers, we find that the high school outcomes of cohorts who enroll during bad times are similar, or if anything slightly worse, than those of cohorts who enroll during good times. Hence, we conclude that our wage differentials cannot be explained through an improvement in *ex-ante* cohort quality due to changes in selection at the time of college entry.

Our measures of academic achievement in university do, however, confirm that cohorts that enroll during bad times are of better quality at the time that they finish their undergraduate studies. Specifically, we find that, in spite of the lack of advantage at the high-school level, the cohorts who enroll during periods of higher unemployment graduate with higher university grades and, remarkably, earn higher wages even conditional on their university grade point average.

Absent any clear evidence of an increase in the quality of education during downturns, we interpret these findings as suggesting that students who enroll in university during bad times improve their human capital acquisition by exerting more effort during their university studies. Effort adjustments in response to adverse economic conditions have been observed in other contexts by Lazear et al. (2016), Mukoyama et al. (2018) and Griffith et al. (2016). Blom et al. (2015) find that students in the US who enroll during worse economic times pursue more challenging majors, which is also consistent with an increase in effort. Given the institutional features that limit students' ability to change majors in the UK, our findings suggest that the increased effort among UK students enrolling during adverse economic conditions manifests itself within, rather than between majors.

We propose three potential channels through which the increase in effort might arise. First, the increase in cohort size due to countercyclical enrollment would lead to increased competition, which might encourage higher effort (see Morin, 2015, for evidence on the relationship between cohort size and effort among male university students). Second, the lack of (part-time) employment opportunities might allow students to dedicate an increased proportion of their time towards their academic studies (see Darolia, 2014; Neyt et al., 2019, for evidence on the relationship between employment and student outcomes). Finally, as suggested by the impressionable years hypothesis (Krosnick and Alwin, 1987), the experience of poor economic conditions during early adulthood might generate a change in attitudes among the students that enroll in bad times, leading them to adjust their effort levels in university. While assessing the relative importance of the three mechanisms is of high interest and policy relevance, it is beyond the scope of this paper and is left for future research.

This paper provides a number of important contributions to several streams of the literature. It is one of the first studies that directly analyzes how selection into college changes over the business cycle, and the first that focuses on the implications of these changes for future labor market outcomes.[5] We contribute to the rich line of research on the implications of macroeconomic conditions for workers' current and future economic achievements (see e.g. Beaudry and DiNardo, 1991; Baker et al., 1994; Gibbons and Waldman, 2006; Hagedorn and Manovskii, 2013), by highlighting the previously disregarded link operating via the increase in college enrollment that is induced by weak aggregate conditions. Our findings also complement the numerous studies on "scarring" effects (Kahn, 2010; Oreopoulos et al., 2012; Altonji et al., 2016b; Liu et al., 2016; Schwandt and von Wachter, 2019) by emphasizing the salience of entering as well as exiting conditions for college students' future payoffs.

Our finding that student effort increases during adverse times, and leads to improvements in future labor market outcomes, has at least two crucial implications. First, it calls into question the external validity of instruments for schooling based on labor market conditions at the time of enrollment. Second, it provides supportive evidence for the interpretation of education as enhancing human capital, rather than merely serving as a signal of individuals' innate ability.

The rest of the paper is organized as follows. Section 2 describes our dataset and our empirical strategy. Section 3 presents the key results in terms of wage outcomes across cohorts and explores various potential mechanisms through which these cohort-level wage differences may arise. Section 4 investigates the merit of the two possible interpretations of our findings in terms of ex-ante ability vs. effort. Finally, Section 5 presents the conclusions.

[5] The only other paper that we are aware of that directly analyzes changing selection into post-secondary education over the business cycle is Alessandrini (2018), who considers the impact of these changes for intergenerational educational mobility.

2 Data and Empirical Strategy

2.1 Background: Higher Education System in the UK

In this paper we focus on individuals whose highest educational achievement is an undergraduate degree.[6] In the UK, students attend secondary school until the age of 16, at which point they take a General Certificate of Secondary Education (GCSE) examination. This marks the end of compulsory education.[7] The GCSE diploma is required to continue on to post-compulsory studies, which involve two additional years of education leading to a standardized school-leaving qualification called 'A-levels' (short for General Certificate of Education – Advanced level). Students can choose the subjects that they wish to take A-level exams in. Most universities require at least three A-levels for admission.

After A-levels, around age 18, students can choose to pursue further studies at university level. Undergraduate degrees in England and Wales normally involve three years of studies, with some exceptions for degrees such as Medicine. In Scotland, the standard length of an undergraduate degree is four years. At graduation, students are classified according to five possible degree classes which, in descending order, are: first-class, second-class upper division, second-class lower division, third class, and ordinary degree otherwise called a "pass". Which degree is awarded depends on the weighted average of the grades obtained during the course of study (with a higher weight usually assigned to grades obtained in the later years).

Throughout the paper, and following the convention in the literature, we use the term 'college graduates' to refer to individuals who are awarded a university-level Undergraduate (Bachelor's) degree.

2.2 Data

2.2.1 Individual-Level Data

Our analysis is based on the UK Quarterly Labour Force Survey (LFS). The LFS is a widely used survey covering around 60,000 households living in the UK in each wave. It is managed by the Office of National Statistics (ONS) and has been conducted quarterly since 1992. We concentrate our analysis on 75 quarterly waves from 1998 to 2016, for which our key variables of interest are available.[8] The LFS presents

[6] This is often referred to as a *first degree* in the British Higher Education system.

[7] In England, compulsory education or training has been extended to age 18 for those born on, or after, 1 September 1997.

[8] This includes all quarters from 1998 to 2016, with the exception of the first quarter of 2004, for which no information on educational levels is available. The wage analysis also excludes the first

several advantages for our analysis, which we describe in further detail below.

Schooling variables – In addition to recording individuals' highest level of education, the LFS also collects information on the year of graduation, the major studied in college and, since the last wave of 2005, two measures of educational performance: the number of GCSE exams passed in high-school and the degree class achieved at the end of university. This unique feature of the data allows us to observe educational performance at different stages for a large sample of individuals from a wide range of cohorts. Moreover, being able to identify the exact moment at which individuals achieve their highest level of education is crucial for our purposes, as it allows us to infer, with a fair degree of accuracy, the point in time when the individual enrolled into tertiary education, and hence the macroeconomic conditions that prevailed at the time of enrollment. This is in contrast to most datasets which only record individuals' highest achieved education level, but not when they obtained this degree. Researchers who use such datasets and are interested in the impact of macroeconomic conditions at the time of college entry (or graduation) must make the assumption that individuals started their studies at the standard age of high-school graduation (see e.g. Blom et al., 2015). This assumption is not innocuous. According to Barr and Turner (2013), only about 54% of undergraduate students in the US were of traditional college age in 2010. Moreover, and importantly for our purposes, cyclical shocks may have differential effects across age groups in terms of post-secondary enrollment, making the assumption particularly problematic for business cycle analysis. Having information on the year of graduation for each individual in our sample is therefore an important advantage of our dataset.

Construction of cohorts by enrollment year – We impute the year of enrollment as the year of graduation minus three for all major categories except for graduates in Medicine for which the normal course of study takes five years. In Scotland, the length of a standard undergraduate degree is four years. Unfortunately, the publicly available LFS data do not provide information on where individuals obtained their undergraduate degree. For the waves from 2001 onward we do, however, know whether individuals were born in Scotland. Analysis of restricted-use LFS data from April-June 2017 supplied by the Data Advice and Relations Team at the ONS shows that nearly 85% of undergraduate degree holders who were born in Scotland also studied at a Scottish university. Hence, when information on the location of birth is available, we impute the year of enrollment as the year of graduation minus four for individuals born in Scotland. We also check the robustness of our results to excluding the Scottish born.

The assignment of enrollment years allows us to group individuals into cohorts according to their year of enrollment, ranging from 1960 until 2010. Although we only observe labor market outcomes after 1998, we are able to infer the business

quarter of 2001, for which no earnings data is available.

cycle conditions that prevailed at the time of enrollment for all of these cohorts. Naturally, the observed labor market outcomes will be affected by time, cohort, and life cycle effects. Section 2.3 provides a detailed discussion of how our empirical strategy identifies the effects of the business cycle conditions at enrollment while accounting for time, cohort, and life-cycle patterns in wages.

Our imputation procedure opens up some concerns of misclassification, as some students might exceed the normal length of their university course. If that is the case, we would be assigning the wrong starting date, and therefore the wrong unemployment rate, to the delayed students. To alleviate these concerns, we compute the relevant unemployment rate at the time of enrollment as the average of the three years preceding the imputed year of enrollment.[9] We also check the robustness of our results when restricting the sample to those who, based on their age at graduation, would not have exceeded the normal length of studies for their degree.

Sample restrictions – We limit our sample in several ways. First, we restrict our analysis to men only in order to avoid any issues of selection into college and into the labor force which could be particularly relevant across older and younger cohorts of women.

As mentioned above, we focus our analysis exclusively on individuals whose highest educational achievement is a Bachelor's degree, hence dropping respondents with either a higher or a lower educational level. Naturally, the composition of this sample varies over time according to selection into university and into post-graduate studies. Variation in the margin of selection into university over the business cycle is precisely the variation that we seek to explore in our analysis, and we discuss our identification strategy in detail in Section 2.3. The fact that we drop individuals with post-graduate studies may introduce selection bias if selection into post-graduate education is correlated to business cycle conditions at the time of undergraduate enrollment. In our data, however, the unemployment rate at undergraduate entry seems unrelated to the probability of enrolling into post-graduate studies.[10]

We also drop observations whose imputed year of enrollment in college is inconsistent (e.g. before the individual turned 16), observations where the age at university completion is over 45, and observations with missing information on their field of study in university. Individuals for whom the year of university entry is less than four years prior to being interviewed are also omitted, as they may still be pursuing

[9] Our results are robust to using shorter windows of time leading up to the year of enrollment. Results are available upon request.

[10] We estimate a linear probability model for the probability of being observed while studying towards a post-graduate degree, controlling for ethnic background, year fixed effects, a quadratic in age, a linear cohort trend, and a set of dummies for location of residence. The effect of our 3-year average measure for unemployment at college entry in this regression is fairly precisely estimated at zero, with an estimated coefficient of -0.002 and a *p-value*$<1\%$. Results are available upon request.

further studies. Finally, we exclude foreign nationals who obtained their college degree before the year in which they arrived in the UK, as they would not have been directly affected by the macroeconomic conditions that prevailed in the UK at the time of their enrollment.

After applying these rules, we are left with a sample of 250,438 individual-year observations for college graduates. Panel A of Table 1 shows descriptive statistics for this 'full sample', which we use to estimate employment probabilities and field of study selection. The columns correspond to graduates by enrollment decade, and statistics for the entire sample are displayed in the final column. Overall, the sample is predominantly white, but ethnic minorities are more prevalent among more recent cohorts. Age at graduation is around 23 overall, but it has increased steadily over the last 50 years.

The table also shows the composition across university majors. To categorize university majors we use UNESCO's International Standard Classification of Education (ISCED), 2013 update. The descriptive statistics show that, through time, the fraction of graduates in Engineering declined, perhaps due to the emergence of related degrees in Information and Communication Technologies, which in the final decade account for 10% of university degrees, while they were largely absent for the first decade. It is also worth noting the upsurge of the share of graduates in Business and Law – from 10 to 21% – and the reduction of the share of graduates in Natural Sciences, that went from 25 to 17% of all male university graduates. The other categories are fairly stable in their share of graduates. It should also be noted that the majority of the graduates in our sample enrolled in the 1980s and 1990s.

Our measure of labor market outcomes is real weekly wages expressed in 2015 pounds. Wage information is not collected in all LFS interviews. The LFS is designed as a rotating panel in which each household is maintained in the sample for five consecutive quarters. Information on wages is collected only in the first and last quarter; hence, earnings questions are only asked of around 40% of the sample at any point in time. Our wage analysis focuses on individuals with relevant wage information who are working full time. Among our sample of college graduates in the relevant waves, the probability of working full time is around 86%. Our restricted 'wage sample' includes 52,612 individual-year observations, as shown in Panel B of Table 1. Wages for the early cohorts tend to be higher, as these are observed at later stages of their life cycle and therefore have, on average, more experience than the younger cohorts. As mentioned, Section 2.3 provides a detailed discussion of how our empirical strategy identifies the effects of the business cycle while accounting for time, cohort, and life-cycle patterns in wages.

For our analysis that considers individuals' academic performance, we must restrict our attention to post-2005 observations. Information from this sample is presented in Panel C of Table 2. High-school performance, measured as the number of

GCSEs, has increased through time. Unsurprisingly, the majority of college graduates belong to the highest high-school achievement category. The table also shows an upward movement in the distribution of university grades, with an increasing proportion of graduates with upper second class degrees, and a dramatic fall in the proportion with either ordinary or third class degrees.

2.2.2 Macroeconomic Conditions at the Time of University Enrollment: Unemployment Rate Data

In order to capture aggregate labor market conditions, we use the national unemployment rate, as measured by the ONS.[11] We consider the national unemployment rate to be the relevant indicator for our population of reference. Wozniak (2010) finds that highly educated workers can smooth labor market shocks through migration more easily than other individuals. This is especially relevant for the UK context where local labor markets are often geographically adjacent. Additionally, given the salience of the national unemployment rate, it is likely that families and individuals take it into consideration when choosing whether to enter college.[12]

Figure 1 plots the UK national unemployment rate for 1958–2016. The Figure shows the well documented increase in unemployment in the 1970's and early 1980's and the negative impact of the economic recession of the early 1990's and the financial crisis of 2008–2009. It also shows that even during more recent periods of strong growth, the very low levels of unemployment that the UK enjoyed in the aftermath of World War II were never recovered. Our empirical strategy, discussed in detail in the following subsection, will control for long-run trends and exploit only shorter-term fluctuations in our data.

[11] See https://www.ons.gov.uk/employmentandlabourmarket/peoplenotinwork/unemployment, last accessed 31/07/2017. The survey-based series has only been available on a consistent basis since 1971. Since our data includes cohorts of university graduates who enrolled between 1960 and 2010, we resort to unemployment figures based on administrative sources for the years before 1971. These are available from Denman and McDonald (1996).

[12] Altonji et al. (2016b) also argue that national economic conditions are likely more relevant for college graduates than local conditions; however, in their analysis they use census division unemployment rates in order to obtain additional variation. While using local, rather than national unemployment rates would also provide us with additional variation for identification in our context, we are limited in our ability to use local unemployment rates due to the fact that (i) we have no direct information on where individuals studied or where they lived in the years leading up to college enrollment, and (ii) local unemployment data is only available for a subset of our sample period.

2.3 Empirical Strategy

The literature on cohort effects specifies labor market outcomes as being a function of: (i) current labor market conditions, (ii) individual labor market experience, and (iii) the cohort that the individual belongs to. Identifying all three factors separately is typically challenging, as fixing two dimensions generally determines the third. For example, when estimating a wage regression with controls for calendar year and time since entry into the labor market, it is not possible to identify cohort effects associated with the year of labor market entry, as this is equal to the calendar year minus the number of years since entry. Similarly, if one controls for calendar year effects and age, it is not possible to identify birth cohort effects.

This identification problem is typically overcome by imposing restrictions on the cohort effects. Hall (1971) and Berndt et al. (1995) suggest dropping one cohort effect and restricting the remaining cohort effects to add up to zero. Oreopoulos et al. (2012), in their analysis of how economic conditions at the time of labor market entry affect career outcomes, exclude two cohort effects from their analysis (see their footnote 10). In a similar fashion, Kwon et al. (2010) implement an identification approach that omits two cohort effects. They specifically choose to omit the effects for the first and the last cohort in their sample, as this allows them to identify the evolution of the non-linear component of the cohort effects, around a (non-identified) long-run linear trend. An alternative approach is to control for one of the factors in a non-linear fashion, given that the multicollinearity arises only among the linear terms. This is the approach adopted by Antonczyk et al. (2018).[13]

In this paper, we are interested in how labor market outcomes vary across cohorts that enroll into college at different stages of the business cycle. This implies that, in our context, cohorts are defined by the year of college enrollment. We would, therefore, not be able to simultaneously identify enrollment cohort effects, calendar year effects, and the effect of years since enrollment. We can, however, simultaneously identify enrollment cohort effects, calendar year effects, and *age* effects. This is due to the fact that not all students enter college immediately after high school. Hence, among individuals of age a observed at time t, there is variation in the enrollment cohort that they belong to, due to the fact that different individuals enroll at different ages (and hence in different years). This is one of the advantages of using the UK LFS, where we have information on when each individual graduated. Many studies in the literature impute the year of graduation based on the normal age of college

[13] Other papers that analyze the effect of entry conditions on future labor market outcomes perform their estimation without controlling for (long-run) trends in cohort effects. In particular, the specification used by Altonji et al. (2016b) to estimate the overall (non-major-specific) effect of economic conditions excludes graduation year fixed effects (though they state that including them does not affect their results). Kahn (2010) also excludes controls for college graduation year when estimating the effects of entry conditions using national unemployment rates.

exit. In such a context, by construction, all individuals of age a observed at time t would be imputed to have enrolled in the same year, and hence there would be no independent variation to allow identification of cohort effects, calendar year effects, and age effects.

The fact that we have variation in the age at enrollment therefore means that we can simultaneously control for: (i) the current stage of the business cycle (captured by calendar year), (ii) potential labor market experience (captured by age), and (iii) cohort effects (without imposing additional restrictions as the previous literature does). Controlling for age (rather than years since graduation) seems reasonable in this context, as all individuals in the sample have the same level of education, and students who graduate at older ages may have accumulated relevant work experience prior to enrollment.

Although we could, in principle, fully identify enrollment cohort fixed effects (due to the variation in age at enrollment), we would not, at the same time, be able to estimate the impact of our primary variable of interest – the national unemployment rate at the time of college entry – as this varies only by enrollment cohorts and would be subsumed by the cohort fixed effects. However, our focus is on the short term fluctuations in cohort outcomes that are systematically related to business cycle conditions at enrollment. Hence, we assume that the long-term component of cohort quality evolves over time in a linear fashion, and we identify the wage effects of enrolling at different phases of the business cycle based on the deviations of cohort outcomes around this linear long-term cohort trend.[14]

Our benchmark estimation takes on the following form:

$$w_{it} = \alpha + \beta U_{c_i} + \lambda_1 a_{it} + \lambda_2 a_{it}^2 + \delta c_i + \tau_t + \gamma x_{it} + \epsilon_{it}, \quad (1)$$

where w_{it} is the labor market outcome of individual i observed in year t, α is a constant term, $\lambda_1 a_{it} + \lambda_2 a_{it}^2$ is a quadratic function of the age of individual i at time t, δc_i is the linear long-term trend in cohort quality, with c_i indicating the year of college enrollment for individual i, τ_t captures calendar year fixed effects (for the year in which the labor market outcome is observed), x_{it} is the remaining set of individual-specific characteristics and ϵ_{it} is a standard error term. β, the coefficient of interest, captures the impact of the unemployment rate at the time that individual i enrolled into college (U_{c_i}). This unemployment rate is measured as the average national unemployment rate in the three years leading to enrollment. Having controlled for long-term cohort trends (as well as age and calendar year effects), the identification of β is driven solely by cross-cohort differences in outcomes that are systematically related to the business cycle conditions experienced at the time of enrollment. In other specifications, we

[14]Other papers in the literature exploit within cohort variation across geographical locations by using regional unemployment rates; however, as discussed above, this is not feasible in our context.

replace the quadratic functional form of age with age fixed effects, and the linear cohort trend with a linear function with discontinuities at certain key points in time.

Our specification hinges on the assumptions that: (1) the unemployment rate at college entry only induces cohort-specific deviations from a long-term trend in cohort quality which evolves smoothly in a linear fashion, and (2) the age profile of labor market outcomes is constant across cohorts (an assumption that is widespread in any standard specification of the Mincerian wage equation). Based on these assumptions and the variation in the age at enrollment, we are able to identify our main coefficient of interest β.

Note that although the inclusion of "non-standard" students (i.e. students who enroll at later ages) is crucial in driving identification in our benchmark specification, in Section 3.2 we show that if we restrict attention to "standard" students and adopt an identification approach akin to what has been used in previous literature, we obtain very similar results.

3 Results: Unemployment at Enrollment and Wages

3.1 Benchmark Results

Our benchmark specification estimates Equation (1) using log real weekly wages as our dependent variable for the sample of college graduate males in full-time employment. The additional control variables included in x_{it} are a race dummy, a dummy for foreign nationals, and a set of 19 region of residence dummies. In all cases, observations are weighted using person weights provided in the dataset, and standard errors are clustered by year of enrollment.

We begin by presenting a specification which does not control for the cohort trend (δc_i in Equation (1)). This specification identifies the effect of unemployment at enrollment using all of the variation over time across enrollment cohorts, without accounting for any long-term trends in cohort effects. This specification is similar to some of the specifications used in the literature to identify the effect of economic conditions at the time of labor market entry (but where we instead focus on economic conditions at the time of enrollment into college), and it does not rely on identification from non-standard students. The results are shown in Column (1) of Table 3. The estimated coefficient on the unemployment rate is positive and statistically significant. The coefficient implies that cohorts that enroll in times when the unemployment rate is 1p.p. higher have wages that are on average 0.8% higher, after controlling for age effects and calendar year effects.

The result in Column (1) might be affected by long-term trends in cohort quality, which may coincide with the overall positive trend in unemployment rates depicted in Figure 1. As discussed above, we are able to simultaneously control for calendar year effects, age effects, and long-run cohort trends. Column (2) shows our benchmark result, where we control for a linear trend in cohort wages, along with quadratic age effects, and calendar year effects, as in Equation (1). Identification of β in this setting is obtained solely from (business cycle related) deviations from the trend across cohorts, within a calendar year, after controlling for common age-wage profiles. In this case we still find that cohorts that enroll in times with worse economic conditions have statistically significant higher average wages.

In order to gain insight into the magnitude of the effect, consider an increase of 3p.p. in the unemployment rate at the time of enrollment – approximately one standard deviation in the sample. The estimated coefficient in Column (2) of Table 3 implies that cohorts who enroll in college when unemployment is 3p.p. higher earn approximately 3.6% more on average. Given average real weekly gross wages in the sample of £890 (in 2015 pounds), this implies that cohorts that enroll when unemployment is one standard deviation higher can expect to earn roughly £32 more per week, or £1,660 more per year, for every working year.

Column (3) verifies the robustness of the results when replacing the quadratic control for age with a full set of age fixed effects. This specification allows wages to vary fully flexibly over the life cycle, while maintaining the identifying assumption that this life cycle variation is common across cohorts. In this case, we still find a positive and statistically significant effect of unemployment at enrollment on current wages.

Column (4) considers whether the result might be affected by changes in tuition fees. In 2006, there was an increase in tuition fees in the UK. This may have changed the patterns of selection into university, with implications for average wage levels across cohorts. The timing of the introduction of the fees could potentially be correlated with the business cycle. To account for this, in Column (4) we add a dummy for the 2005 enrollment cohort (where the composition could differ in anticipation of the introduction of the new fees) and a dummy for the post-2006 enrollment cohorts, who enroll during the time where tuition fees were higher.[15] The results show that allowing for these discontinuities in outcomes across cohorts due to tuition fees does not affect our main result.

In Column (5) we verify the robustness of our results to excluding certain cohorts. Specifically, we repeat our estimation using a restricted sub-sample which excludes the cohorts that enroll from 2005 onwards, which may be affected by the change in tuition fees, as well as the cohorts that enroll prior to 1971, given that the way in which

[15] Tuition fees were further raised in 2012, but recall that we restrict the sample to cohorts who enrolled up to the year 2010 in order to have sufficient post-graduation wage observations, so these later cohorts are not part of our analysis.

the national unemployment rate is constructed changes in that year. Restricting the estimation to the sub-sample of the 1971–2004 cohorts also allows us to check the validity of our results by focusing only on the cohorts that we observe during a substantial portion of their life cycle (i.e. excluding the early cohorts, which we only observe at older ages, as well as the more recent cohorts, which we only observe at younger ages). Reassuringly, Column (5) of Table 3 indicates that the results for this restricted sub-sample are very similar to our baseline results.[16]

Column (6) excludes the control for region of residence, which might be considered an inappropriate control variable given that the effect of unemployment at enrollment might partly operate through the ex-post choice of region of residence. This changes the estimated coefficient of interest only marginally.

We have further verified that our coefficient of interest remains positive and statistically significant if we allow for discontinuities in the cohort trend across enrollment decades, or if we allow for a quadratic (rather than a linear) cohort trend.[17] Overall, our results consistently indicate that the average wages of cohorts of students who enroll into university when aggregate economic conditions are poor are higher than those of cohorts who enroll during better economic conditions. This result is striking, given that enrollment into university tends to increase when macroeconomic conditions deteriorate, which would lead us to expect worse selection in terms of quality for these cohorts. Instead, our results show that the cohorts that enroll during worse macroeconomic conditions end up performing better in the labor market. In Section 4 we analyze whether the pattern is likely to be driven by changes in selection into higher education over the business cycle, or by behavioral changes among students. Before this, we show that the fact that we use non-standard students for identification is not driving our results, and we rule out several potential explanations for the pattern that we find.[18]

[16] Note that in all other specifications we have a total of 51 clusters, which is above the rule-of-thumb thresholds considered appropriate for reliable inference using a standard cluster adjustment (see e.g. Cameron et al., 2008; Angrist and Pischke, 2009). For the specification in Column (5) of Table 3, which only uses 34 clusters, we have verified that our estimated coefficient of interest remains statistically significant at the 1% level if we estimate the standard errors using wild bootstrap methods.

[17] Results are available from the authors upon request.

[18] As mentioned above, our imputation of the year of enrollment assumes that all individuals born in Scotland study in Scotland and hence complete their degrees over a four year period. Based on the analysis of restricted-use LFS data provided by the ONS we know that this assumption is incorrect for around 15% of the Scottish born sample. Hence, in Appendix Table A.1, we replicate our main results for the period from 2001 onwards (during which information on location of birth is available), and show that excluding the Scottish-born has no noticeable effect on our coefficient of interest. Note also that some individuals born in England and Wales would have the wrong year of enrollment imputed if they studied in Scotland. However, the ONS analysis mentioned above shows that only around 2% of English and Welsh undergraduate degree holders obtained their degrees in Scotland, so this would only be of minor concern.

3.2 Excluding "Non-Standard" Students

The source of variation that enables us to identify the effect of unemployment at enrollment, while simultaneously controlling for age, cohort, and time effects is the fact that individuals enroll into college at different ages. The higher wage observed among cohorts who enroll during times of higher unemployment may be reflecting differential selection of "non-standard" students (i.e. those who enroll into university at later ages) among these cohorts. In this section we explore whether this is driving our results, or whether similar patterns are observed when we focus only on "standard" students (i.e. those who who enroll at age 18 or 19).

Column (1) of Table 4 reproduces our baseline estimation using only individuals who enrolled into college at age 18 or 19, thus excluding those who enroll into college after some time in the labor market. The results for this sample are very similar to our baseline estimation.

In Column (2) we only consider individuals who enrolled at age 18. In this case, year of enrollment is a perfect function of calendar year and age, so we are unable to control for all three dimensions, and we exclude our linear cohort trend. The results that we obtain are remarkably similar to those from the baseline sample. The same is true when we restrict the sample to individuals who enrolled at age 19 in Column (3).

As noted by Kwon et al. (2010), in a setting where cohort is a linear function of calendar year and age, the deviations of the cohort effects from a (non-identified) linear trend can still be identified by estimating a regression that controls for age, calendar year, and cohort fixed effects, where the first and last cohort effects are set to 0. In order to provide further evidence of the impact of economic conditions at enrollment among "standard" students, we implement this procedure using individuals who enroll either at age 18 or at age 19.

In Figure 2 we plot the cohort effects estimated with this methodology for the two sub-samples of individuals who enrolled at age 18 and at age 19, respectively, together with the average unemployment rate for our period of interest. Both lines suggest that, even when focusing only on individuals who chose to enroll into college without delays, the correlation between wages and unemployment rate at entry is positive. The correlation between the cohort effects and the average unemployment rate is 0.50 and 0.74 for the 18 and 19 year old group, respectively.

Overall, we conclude that the positive correlation between unemployment at enrollment and cohort wages that we have identified is not (solely) driven by the fact that we include non-standard students in our analysis.

3.3 Additional Results

Before delving deeper into the potential mechanisms that might account for the wage differences across cohorts that we have documented, we explore some additional features of this relationship in Table 5. First, we consider whether the effects of unemployment at enrollment vary with labor market experience. Enrolling in times of high unemployment may generate an initial wage gap after graduation which may fade away over time. In Column (1) of Table 5 we add an interaction term between the unemployment rate at the time of enrollment and years since graduation. This allows us to distinguish between the short and long term effects of enrolling during times of high unemployment. We find that cohorts of graduates who enrolled during times of higher unemployment have a large initial wage advantage, which only slowly disappears with labor market experience. The rate of decline is quite slow, so we focus on the overall average effect in the remainder of the paper.

So far we have imposed a linear relationship between unemployment at enrollment and wages. In Column (2) we relax this assumption and estimate our benchmark model, replacing the linear average unemployment rate with dummy variables for quartiles of the unemployment at enrollment distribution. Our results show noticeably larger effects of unemployment in the top two quartiles. Cohorts entering university when unemployment is around 8% – the average unemployment rate for the third quartile – earn around 6.7% higher weekly wages than those entering when unemployment is in the bottom quartile, while for the highest quartile – when unemployment is around 10% – the positive difference is 7.3%. Overall these results show that the size of the unemployment shock matters for subsequent outcomes. Unemployment at entry has markedly stronger effects on labor market outcomes at high levels of unemployment.

One potential explanation for the cross-cohort wage differences that we have identified could be selection into employment. If cohorts who enrolled during worse economic conditions have lower employment probabilities, it may be the case that the subset of full-time workers from these cohorts is more positively selected than among cohorts who enroll into university during better aggregate conditions. To check whether this is the case, in Columns (3) and (4) we estimate regressions analogous to our baseline specification from Column (2) of Table 3, but where the dependent variable is a dummy which is equal to one if the individual is in full-time employment. As mentioned in Section 2.2.1, earnings questions are only asked when individuals are in their first and fifth wave in the LFS. For the linear probability model estimation in Column (3) we restrict the sample to individuals in these waves, so that the sample is directly comparable to the one used in our wage equations. The probability of full-time employment within this sample is around 86%. The results in Column (3) show that there is no statistically significant relationship between aggregate conditions at the time of university enrollment and the probability of working full time. Although positive, the estimated coefficient is quite small. In Column (4) we extend the sample to all waves, hence including observations from waves in which wage questions are not asked. Naturally, this increases the sample size substantially. The results in Column (4) show that the coefficient of interest in this sample is similar to the one estimated in Column (3), and also statistically insignificant. Hence, we conclude that there is no strong evidence that the difference in cohort wages that we observe is driven by differential selection into full-time employment.

In Table 6 we explore whether the positive wage effect that we find in our baseline specification is concentrated in certain parts of the distribution. To do this, we run a set of quantile regressions analogous to Column (2) in Table 3. The results for each of the conditional deciles of the log real wage distribution are presented in Table 6. The estimated coefficients are positive and statistically significant throughout the wage distribution. Thus, it seems that the whole distribution of wages shifts up for cohorts who enroll during worse economic conditions. The largest effects are found at the 70th and 80th percentiles, suggesting that the effects are slightly larger towards the top half of the distribution.

3.4 Potential Channels

In this section we explore three potential channels through which the wage differences documented above might arise: variation in economic conditions at the time of graduation, changing selection into different fields of study, and changing selection into occupations or industries.

3.4.1 Economic conditions at time of graduation

There is strong evidence in the literature that economic conditions at the time of graduation have large and long-lasting effects on labor market outcomes for university graduates (Kahn, 2010; Oreopoulos et al., 2012; Altonji et al., 2016b; Liu et al., 2016).[19] Our finding regarding differences in average cohort-level wages could potentially arise if cohorts that enroll in bad times tend to graduate in good times, and hence avoid these negative graduation effects. This would be the case if the unemployment rate at enrollment were negatively correlated with the unemployment rate at graduation.

In Figure 3 we plot the correlation between unemployment rates at the time of enrollment (college entry) and at the time of graduation (college exit) experienced by

[19] See also Schwandt and von Wachter (2019), who show that adverse effects are also observed for workers without a college degree.

each cohort. The two unemployment rates are clearly positively correlated (although less so for higher levels of unemployment). This implies that individuals who enroll in bad times tend to, on average, also graduate during relatively bad times, which would go against the intuition described above.

In order to investigate this more formally, we estimate a regression analogous to that in Kahn (2010) and other papers that analyze the scarring effects of graduating during bad times. Specifically, we control for the unemployment rate at the time of graduation, as well as the interaction of the unemployment rate at graduation with time since graduation. To this specification, we add our main regressor of interest, the unemployment rate at the time of enrollment. The results are presented in Column (1) of Table 7. Consistent with the scarring effects literature, in this specification we find that the unemployment rate at the time of graduation has a negative and statistically significant effect on wages, and this wage penalty is slowly eroded as years since graduation increase. Our effect of interest, however, remains robust. Hence, we conclude that, even conditional on economic conditions at graduation, cohorts that enroll at times when unemployment is higher have higher average wages.

3.4.2 Major choice

There is also recent evidence in the literature suggesting that economic conditions at the time of enrollment have an impact on students' field of study preferences and choices (Bradley, 2012; Goulas and Megalokonomou, 2015; Blom et al., 2015). It is also well known that wages vary substantially across majors (e.g. Altonji et al., 2012; Lemieux, 2014; Altonji et al., 2016a). Therefore, a potential explanation for the wage differences that we have documented would be that students who enroll when economic conditions are poorer tend to select into higher paying majors, thus increasing average wages at the cohort level.

To explore evidence for this mechanism, we proceed in two stages. First, we analyze whether we observe changes in field of study choices over the business cycle in our dataset. To the best of our knowledge, this is the first paper to explore the effects of the business cycle on the composition of majors in the UK. Then, we return to our wage regression to determine whether changes in the field of study composition across cohorts can account for the differences in wages.

To determine whether the composition of fields of study varies according to the business cycle, we estimate a series of linear probability models of students' major choices. The models are estimated separately for each major category. As individual controls we include race and nationality. In order to account for long-run changes in the composition of majors across cohorts, we allow for a quadratic cohort trend in the enrollment probability into each major. As before, our regressor of interest is the average unemployment rate in the three years leading up to enrollment.

We plot the results for the estimated coefficients on the unemployment rate at the time of enrollment in Figure 4. Our estimates suggest that in periods of higher unemployment, more students select into Engineering and out of Business, Education and Information and Communication Technologies. The impact of the unemployment rate at time of enrollment is significantly different from zero at the 5% level for four out of the nine categories. However, the estimated effects are small. Our estimates imply that a 5 percentage point increase in the national unemployment rate – a historical swing, only experienced twice in the last 55 years in the UK – would increase the share of graduates in Engineering, the most responsive category, by around 4 percentage points – a fairly modest change.[20] Moreover, although Engineering – which is clearly a high-paying field – grows in recessions, other high-paying fields such as Business, Administration and Law tend to shrink. It is also not obvious what the changes in field of study composition would imply for cohort-level wages, given that marginal students who change their field of study decisions due to the business cycle might not earn wages that are similar to the average wages in their new field of choice.

In order to determine more directly whether changes in the field of study composition explain the differences in wages across cohorts, we return to the wage regression from Table 3 and add controls for fields of study. Specifically, we replace the simple calendar year fixed effects with fully interacted field of study-calendar year fixed effects. This controls for changes in the return to different fields and limits identification to variation within field-year cells. To the extent that the effect that we were finding was due to differences in field of study composition and the differences in rewards across fields, these new fixed effects should eliminate our effect.

The results are displayed in Column (2) of Table 7. Interestingly, adding these field-specific calendar year fixed effects does not eliminate our result of interest. Compared to the estimated effect of the unemployment rate in Column (2) of Table 3, the coefficient falls by a little over 10%, suggesting that the effect of changes in major composition on average cohort wages is relatively small.

Appendix Table A.2 explores whether the positive wage effect is concentrated within certain fields of study. Column (1) shows results that are analogous to Table 3, Column (1), but where all variables are fully interacted with field dummies (except the race, nationality and region of residence dummies, which are not shown in the table for brevity). The results show that cohorts that select into university during periods of higher unemployment earn higher wages *within all fields*: The point estimates are always positive, although not always statistically significant. Interest-

[20]This contrasts with the results for the US in Blom et al. (2015), which show a much stronger responsiveness of major composition to the business cycle, and is likely due to the fact that selection of majors is much more rigid in the UK system, where students' choices are more limited by their course of study during their A-levels. It may also reflect less flexibility at the departmental level to change enrollment as a response to changes in application volumes.

ingly, the results are statistically significant in a subset of high-paying fields, including Natural Sciences, Mathematics and Statistics, and most notably, Engineering. This implies that the cohorts selecting into these highly remunerated fields when aggregate economic conditions deteriorate actually have higher average wages than those who select into these fields in better times. Again, this contrasts with our expectation that a field like Engineering would attract lower quality marginal students as it tends to expand in response to worsening aggregate economic conditions.

The remaining columns in Appendix Table A.2 explore variations in the specification and find consistent results.[21] Overall, the results provide robust evidence that the increase in wages observed for cohorts who select into college during worse economic conditions is *not* driven by reallocation across fields of study. Instead, there appears to be an improvement in cohort quality within many fields, particularly so within high-paying fields such as Natural Sciences, Mathematics and Statistics, and Engineering.

3.4.3 Occupation and industry sorting

The wage differential that we have found for cohorts who enroll in university during worse macroeconomic conditions could be, to some extent, driven by differential sorting into higher paying occupations or industries. For example, Liu et al. (2016) show that business cycle conditions at graduation have important implications for the quality of graduates' initial industry match, and this can explain some of the persistent wage losses from graduating in a recession.

Here we explore the extent to which differences in the occupation and industry composition of different cohorts can explain the wage differences that we have identified. We do this by adding a set of controls for occupations and industries and determining the extent to which the coefficient on the unemployment at enrollment is reduced.

In Column (3) of Table 7 we add a set of nine broad occupation dummies, interacted with calendar year. This accounts for variation in the return to different

[21] Specifically, Column (2) controls for an overall linear trend in cohort quality, which would capture any general cohort trend that is common across fields (for example, because of changes in the selection of college-goers in general). Column (3) replaces the general cohort trend with field-specific linear trends in cohort quality. In Column (4) we add a full set of cohort dummies. In this case, the effect of unemployment on overall cohort quality is no longer identified; this is absorbed by the cohort dummies. Instead, what we can still identify is the effect of unemployment on *relative* wages across fields. The results once again suggest differential wage gains among college-goers in higher-paying fields. Finally, Column (5) controls for field-specific effects of economic conditions at the time of graduation (i.e. field-specific impacts of unemployment at graduation, and field-specific interactions of this unemployment rate with years since graduation), along with an overall linear trend in cohort quality.

occupations over time.[22] The coefficient on unemployment at enrollment is still statistically significant, implying that cohorts who enroll into university during periods of higher unemployment have higher wages, even within occupations. The slight reduction in the magnitude implies that only a small part of the cohort-level wage differences are due to differences in selection into different occupations.

As Liu et al. (2016) emphasize, an important determinant of wages is the quality of the job match with respect to an individual's field of study. In other words, occupational wage premia may differ significantly across individuals with different types of degrees (see also Lemieux, 2014). In order to account for this, in Column (4) of Table 7 we further interact our occupation-calendar year dummies with a full set of field of study indicators. Any remaining effect of unemployment at enrollment would capture cohort-level differences within occupation-field-calendar year cells. The results in Column (4) show that the coefficient of interest falls by about one-third relative to the baseline estimate in Column (2) of Table 3. This implies that, remarkably, the majority of the wage variation that we identify occurs within occupation-field-calendar year cells.

Columns (5) and (6) of Table 7 repeat the analysis using ten broad industry categories instead of the occupation groups. The results are similar with regards to industry sorting.

4 Understanding the Wage Differences: Ex-Ante Selection or Increased Effort?

Our results so far provide strong evidence of ex-post differences in the average quality (unobserved ability) of cohorts that enroll at different points in the business cycle. In this section, we explore whether this can be explained by better selection among students who enroll during poor economic conditions – implying that these cohorts are of better quality *ex-ante* – or whether the differences in quality only arise *ex-post*.

Carneiro et al. (2011) and Carneiro and Lee (2011) show that increases in college enrollment in the US between 1960 and 2000 led to a decline in the average quality of college graduates. A similar logic would lead us to expect that the expansion of enrollment that occurs during bad times would be associated with a lowering of the average cohort-level ability. The additional marginal students who enroll in bad times may not be as well-suited for higher education and may even negatively impact the achievements of their peers. However, this is in stark contrast with our main finding

[22] Having these occupation-time interactions also implies that we do not need to be concerned about changes in the occupational coding schemes over time, given that identification is solely within occupation-year cells.

that the cohorts that enroll during bad times receive above-average wages.

While average cohort quality is not directly observable, our data includes information on school performance before college entry and during college. This can be used to shed some light on how the observed ex-ante and ex-post cohort ability varies with the economic conditions at entry. The two measures of educational performance that we will exploit are: (i) the number of GCSE exams passed in high school, an *ex-ante* measure of performance providing us with an indication of the average level of cohort quality at entry;[23] and (ii) the "degree class" achieved in university, which is a function of students' Grade Point Average, and hence provides us with an indication of the cohort's *ex-post* quality as they exit college and enter the labor market.

4.1 Ex-Ante Selection: Academic Performance in High School

We begin by analyzing how the average *ex-ante* quality of cohorts varies, by determining whether cohorts who enroll at different points in the business cycle differ in terms of the number of GCSEs that they passed in high school. The LFS records the number of GCSEs passed with a grade of C or above using the following interval categories: one to two, three to four, five to seven, or more than eight. We construct a continuous measure using the mid-points of each interval (where we assign a value of nine for the "more then eight" category), and we also present results based on linear probability models, where we use a dummy for each of the possible intervals as the dependent variable.[24]

The regression results are presented in Table 8. In all specifications, we allow for a linear trend in the outcome variable across cohorts, which controls for long-term patterns in GCSE achievement levels. All regressions also include individual-level controls for race, nationality, and region of residence at the time of the survey. Column (1) shows the estimates from the regression that uses the continuous measure as the dependent variable, while the remaining columns show results based on the linear probability regressions for each possible outcome. The estimates show that cohorts entering college in high unemployment years have on average passed *fewer* GCSE exams than those going in boom periods. This is driven by a lower probability of having passed eight or more GCSEs, as seen in Column (5), and is statistically significant at the 5% level.

[23] A variable recording the number of A-levels, another measure of pre-university achievements, is also available in the LFS, but it has very limited granularity, only recording whether the individual has zero, or one or more A-levels. Given that a key prerequisite for university admission is the number of A-levels, this variable presents almost no variation in our sample.

[24] GCSE exams were introduced in 1988, replacing the O-level exams in England, Wales and Northern Ireland. For individuals who finished high school before 1988, the LFS records the number of O-level exams passed with a grade of C or above.

Consistent with our expectation from existing evidence on selection into education, our estimates suggest that the average ex-ante quality of cohorts who enter college during periods of higher unemployment is, if anything, lower than the average quality of those who enter during periods of lower unemployment.[25] Hence, our results do not support the hypothesis that the positive wage effects that we find for these cohorts can be explained by more positive selection among these cohorts in terms of their *ex-ante* academic achievements.[26] We next explore whether the positive wage effects can be explained by better average quality at the time of university exit by analyzing cohorts' academic performance in college.

4.2 Ex-Post Quality: Academic Performance in University

In order to analyze ex-post cohort quality we focus on individuals' degree classifications obtained in university which, as mentioned in Section 2.1, are a function of students' university grades. The UK uses a system of external examiners which aims at standardizing degree classifications and making them comparable across UK universities. As with the GCSE variable, we perform our analysis using a continuous measure which ranges from one to five based on the five degree class categories, where one corresponds to the lowest GPA outcome ("pass") and five to the highest ("first class"). We also present results based on linear probability models for each of the possible degree class outcomes. As before, we allow for cohort trends in the outcome variable. These cohort trends are meant to capture overall trends in the quality of university students and/or in "grade inflation" patterns.

The results based on the continuous degree class measure are presented in Table 9. All specifications include individual-level controls for race, nationality, and region of residence at the time of the survey. Standard errors are clustered by year of enrollment. We allow for a quadratic trend in degree class outcomes across cohorts. The results in Column (1) indicate that cohorts who enroll during times of higher unemployment graduate, on average, with higher GPAs. This provides a first piece of evidence supporting the idea that these cohorts end up being of better quality by the end of their studies.

The specification in Column (1) does not control for the fact that some students

[25] The reason why we do not find stronger evidence of negative selection during downturns may be driven by the fact that we only observe individuals who actually complete their college degrees. Even though the *enrollment* cohort may become significantly more negatively selected in downturns as enrollment expands, many of the marginal lower ability students might not complete their degree, and hence the overall ex-ante quality of the *graduating* cohort may not be much affected. Evidence from the US shows that expansions in enrollment rates are not necessarily matched by increases in graduation rates, particularly among lower ability students (Bound et al., 2010).

[26] We also check whether cohorts enrolling in periods of high vs. periods of low unemployment differ in terms of observable characteristics and find no strong evidence of any meaningful differences.

return to university at older ages. Since older students might be more mature and/or motivated to pursue their studies, in Column (2) we add a control for age at graduation. Our coefficient of interest remains unaltered. As the grade distribution is likely to differ across college majors, in Column (3) we add field of study fixed effects. This would control for the possibility that individuals who decide to enroll into college in times of higher unemployment might select majors where higher grades are easier to achieve. Adding field fixed effects, however, has no impact on our main coefficient (consistent with our earlier finding of limited reallocation across fields over the business cycle). In Column (4) we introduce a full set of field-specific linear trends in cohort effects, thus allowing for different trends between fields either in terms of cohort quality or in grading leniency. Again, the coefficient of interest remains positive and significant. Finally, in Column (5) we add a full set of dummies for the number of GCSEs passed in high school (in intervaled categories, as discussed in the previous subsection), and their interaction with a linear cohort trend, thus controlling for the (potentially time-varying) relationship between high school and university outcomes at the individual level. Not surprisingly, given the evidence that cohorts who enroll during periods of higher unemployment are more negatively selected in terms of their GCSE achievements, controlling for *ex-ante* achievement measures increases the positive *ex-post* achievement gap in favor of high unemployment cohorts.

Appendix Table A.3 further explores the positive correlation between unemployment at enrollment and university GPA by running separate linear probability regressions for each possible degree class outcome. We focus on the specification in Column (4) of Table 9, which allows for field-specific linear trends. The results show that the positive GPA effect arises from the fact that cohorts that enroll during times of higher unemployment are significantly more likely to graduate with a first class degree, everything else equal, and significantly less likely to graduate with a third class degree.

Given this evidence, one might expect that the higher average wages for cohorts who enroll during periods of higher unemployment might be explained by their better academic performance in university. To determine whether this is the case, we return to our wage regressions, but now add controls for individuals' degree classifications. Given that the degree classification information is only available for a subset of recent years, we first present our baseline estimates using the same specification as before, but restricting the sample to individuals for whom we have non-missing information on degree classification. The results are presented in Column (1) of Table 10. The results for this sub-sample are similar to those for the baseline sample.

In Column (2) we add controls for degree classification, in the form of a full set of degree class fixed effects. Remarkably, the estimated coefficient on the unemployment rate at enrollment does not change in magnitude. In Column (3) we replace the simple degree class fixed effects with fully interacted degree class and calendar year fixed effects. This allows the return to different degree classes to vary over time. Our coefficient of interest remains unaltered. Finally, in Column (4) we control jointly for degree classification and re-shuffling of individuals across fields, by including field-specific calendar year fixed effects along with the degree classification fixed effects. Again, our estimated coefficient of interest remains unchanged.

This implies, surprisingly, that the increased attainment in terms of degree classification does not account for the wage differences across cohorts either. Even conditional on degree class, students who enroll into university during times of higher unemployment earn higher wages. Therefore, the higher average wages of these cohorts seem to be driven by unobservable skills not captured by observed academic ability. Moreover, these unobservable skills would need to explain both higher wages and higher educational achievements for cohorts of individuals whose academic performance in earlier years (prior to college entry) is at best equal to, and possibly worse, than that of cohorts enrolling in periods of economic expansion.

4.3 Discussion: Increased Effort

Our findings suggest that the cohorts who enter university during poor economic conditions more than compensate for their initial lower quality and obtain higher grades in university, as well as earning higher wages conditional on their grades. What could account for this improvement in cohort quality that arises during their university years? One possibility is that the quality of education improves during downturns. This could occur if there is an improvement in instructor quality due to changes in selection into (or retention in) higher education teaching following periods of high unemployment. Böhm and Watzinger (2015), for example, find an improvement in selection into academia among PhD economists graduating in a recession.[27] On the other hand, there is evidence that government expenditures on education decrease during periods of high unemployment. Data on expenditures on tertiary education in the UK over the period 1971–2015 from UNESCO shows that the correlation between the expenditures and the national unemployment rate is -0.13 with a p-value of 0.43, implying that there is no statistically significant relationship between the two variables. If anything, the UK government tends to invest less into tertiary education during recessions, not more. Kane et al. (2005) and Barr and Turner (2013) also find evidence of declining public expenditures on education during downturns in the US. These funding reductions might offset any potential gains derived from changes in instructor quality.

Given the lack of clear evidence pointing towards an improvement in the quality of education during downturns, we interpret our results as indicating that there is

[27]See also Nagler et al. (2015), who find evidence of higher effectiveness among primary school teachers who select into the teaching profession during downturns.

an increase in the effort that the cohorts that enroll during bad times exert during their university studies. The results from the quantile regressions presented in Table 6 also seem consistent with this idea: The increase in effort would move the entire distribution of labor market outcomes upwards, but the lower ex-ante ability composition would imply that the wage gains are smaller at the lower quantiles of the distribution. Effort adjustments in response to adverse economic conditions have also been observed in other contexts. Lazear et al. (2016) find that the Great Recession induced US workers to exert more effort and that this increased effort explains most of the gains in productivity experienced by US firms in that period. The results in Blom et al. (2015), which show that students in the US who enroll during worse economic times pursue more challenging majors, can also be interpreted as reflecting increased effort during downturns among university students in the US. Given the institutional features that limit students' ability to change majors in the UK, our findings suggest that while the increased effort among US students enrolling during adverse economic conditions manifests itself through major changes, the analogous adjustment in effort among UK students manifests itself within, rather than between majors.[28]

Why would cohorts who enroll during periods of higher unemployment exert more effort during their studies and in the labor market? We believe that there are at least three potential explanations.

1. Increased competitive pressure – The fact that university enrollment tends to be countercyclical implies that individuals who enroll in university during times of higher unemployment would be part of larger cohorts. This would mean that in order to excel in class – particularly if grading is to some extent done on a curve – students would have to exert extra effort. This extra effort could translate both into higher grades, and even if not reflected entirely in their grades, in higher human capital accumulation that is later reflected in the form of higher wages, conditional on university grades. Evidence of effort adjustments in response to changes in cohort size is provided in a different context by Morin (2015), who exploits a natural experiment that exogenously led to a substantial increase in the size of an enrollment cohort at Ontario universities, and shows evidence of an increase in the relative effort exerted by male students as a reaction to increased competition for university grades.[29]

2. Increased focus on academic achievement due to lower employment opportuni-

[28]Effort adjustments during downturns have been documented in very different contexts by Mukoyama et al. (2018), who find that search effort increases during downturns, and Griffith et al. (2016), who find that individuals adjust their food expenditures while maintaining similar nutrition levels by increasing their shopping effort during the Great Recession.

[29]Roth (2017) finds that apprenticeship graduates who are part of larger cohorts in Germany are able to find jobs faster, without compromising the quality of the jobs that they take. A number of papers in the literature instead find that overall cohort sizes tend to be correlated with worse labor market outcomes, mainly attributed to the saturation of the labor market; see for example Welch (1979); Berger (1985); Wright (1991); Brunello (2010); Agarwal et al. (2017).

ties – Another reason why effort may increase for cohorts who enroll during poorer economic conditions is the fact that their opportunities for (part-time) employment may be reduced during their studies, hence allowing them to dedicate a larger proportion of their time to their academic activities. Using data from the American Time Use Surveys, Kalenkoski and Pabilonia (2012) show that working time crowds out time devoted to school-related tasks among high school students. Stinebrickner and Stinebrickner (2004, 2008) show that study time has an important effect on grades and other educational outcomes, while Darolia (2014) and Neyt et al. (2019) find that working has a negative impact on students' academic performance.

To explore whether this mechanism might be at play, we focus on individuals who are surveyed in the LFS while they are full time students, and test whether poor labor market conditions are correlated with lower employment rates among this group. The sample used for this set of regressions differs from that used in the previous analysis as here we look at full-time male university students who are observed in the survey while still at university. In the absence of retrospective information on labor market participation, we are forced to restrict our analysis to the period 1998-2015 directly covered by the LFS. The results of this analysis are presented in Appendix Table A.4. We find that a 1p.p. increase in the current unemployment rate is associated with a 1.6–2.2p.p. increase in the probability that a student is not working. These results suggest that cohorts enrolling in a trough might indeed dedicate more of their time to their education, since it is harder for them to find a part-time job while studying.

3. Changing attitudes – The experience of reaching early adulthood during a time of poor macroeconomic conditions may have a direct impact on the attitudes of individuals who select into college during bad times. This interpretation is consistent with a social psychology hypothesis known as the "impressionable years hypothesis" (Krosnick and Alwin, 1987), which suggests that core attitudes, beliefs, and values crystallize during early adulthood. This hypothesis has already proven useful for explaining differences across cohorts in preferences for redistribution and risk attitudes (Giuliano and Spilimbergo, 2014; Malmendier and Nagel, 2011), and in explaining how individuals form expectations about inflation (Malmendier and Nagel, 2016). Following a similar logic, we hypothesize that individuals who select into college during bad times may be particularly susceptible to concerns regarding economic outcomes, and may thus be particularly motivated to excel in their studies. The higher grades and wages that we identify for these cohorts would be consistent with a change in their educational approach due to their experience of poor economic conditions during their key impressionable years.

While it would be tempting to further explore the evidence for this type of channel using data on high-school graduates who decide not to enroll into college (as they would also be impacted through the experience of poor economic conditions during early adulthood), an analysis of this type would be challenging. For individuals who choose to enter the labor market directly after high school, the labor market conditions that they experience during their late teenage years (which might cause an impression on their attitudes) would be the same conditions that they experience when entering the labor market. It would therefore not be possible to separately identify business cycle impacts due to potential changes in attitudes from the impact of the conditions at entry among this sample.

Overall, although we are unable to provide direct evidence of a change in effort among cohorts who enroll during bad times, we believe that there are several pieces of evidence which make this interpretation quite plausible. This has at least two crucial implications for the literature. First, variables such as average wages or unemployment rates, often at the local level, have been widely used as instruments for schooling (Cameron and Heckman, 1998; Cameron and Taber, 2004; Carneiro et al., 2011, 2013), given their potential impact on the opportunity cost of education. Our results imply that unemployment at choice affects later wages by inducing increased effort during university among those who choose to enroll. These individuals would be the "compliers" in the instrumental variable (IV) setting. As IV strategies identify Local Average Treatment Effects (LATE) for the compliers, the estimated effect would include the effort boost, which would not be present for other cohorts. Hence, generalizing the estimates of the returns to schooling obtained from this IV strategy for the broader population would seem problematic.

Second, by underscoring the importance of effort on later outcomes, we contribute to the debate on whether obtaining an educational degree increases individuals' human capital or merely serves as a signal of their underlying innate (predetermined) ability – a persistent debate in the literature on the returns to education (Groot and Oosterbeek, 1994; Weiss, 1995; Chevalier et al., 2004). Our results provide supportive evidence for the interpretation of education as enhancing human capital. A signaling model would be able to rationalize our results only if employers would interpret the choice of enrolling into tertiary education in a bad economy as a signal of higher ability, which seems highly unlikely.

5 Conclusions

Economic downturns tend to attract additional students into higher education. Economic intuition would suggest that these marginal students would reduce the average wage outcomes among cohorts who enroll in college during bad times. Our findings, based on UK data, show exactly the opposite: Cohorts who enroll in college during periods of higher unemployment earn significantly higher wages ex-post. This wage difference is not explained by changing selection into employment, by differences in economic conditions at the time of graduation, or by changes in the selection of fields of study, occupations or industries among college graduates. Instead, we find evidence that suggests that there is a genuine improvement, during their college years, in the quality of the cohorts who select into college during adverse macroeconomic times. This is reflected both in better college degree attainment and in higher wages, conditional on GPA, and it arises in spite of the fact that these cohorts are not more positively selected in terms of their high school outcomes.

We interpret these results as reflecting an increase in effort while at college among students who enroll in times of higher unemployment. Although the specific drivers of this increase in effort merit further investigation, we hypothesize that this may be due to increased competition, reduced opportunities for part-time employment, or changes in attitudes consistent with the impressionable years hypothesis from social psychology. Devising empirical strategies to identify these different channels would be a promising avenue for future research.

Regardless of the driving force behind the improvement in the academic and labor market outcomes for those who start higher education in bad economic times, our findings send a clear signal to policymakers that it is not a good idea to limit funding for education or curb enrollment to tertiary-level education during a recession.

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Table 1: Summary Statistics, by Decade of College Enrollment

	Enrollment Decade					
	1960s	1970s	1980s	1990s	2000s	Total
Panel A: ***Full sample***						
White	0.96	0.94	0.91	0.87	0.82	0.89
	(0.20)	(0.24)	(0.29)	(0.33)	(0.39)	(0.31)
Foreign	0.09	0.08	0.09	0.11	0.10	0.10
	(0.29)	(0.27)	(0.28)	(0.31)	(0.30)	(0.29)
Age at graduation	21.98	22.54	23.18	24.15	24.53	23.56
	(1.63)	(2.73)	(4.00)	(4.98)	(5.39)	(4.43)
Unemp at enrollment	2.05	4.32	9.76	8.44	5.37	7.01
	(0.28)	(0.92)	(1.78)	(1.10)	(0.47)	(2.71)
University major:						
Health & Welfare	0.06	0.06	0.04	0.04	0.05	0.05
	(0.24)	(0.23)	(0.20)	(0.21)	(0.23)	(0.22)
Soc. Sci., Journ. and Info.	0.11	0.12	0.11	0.11	0.12	0.12
	(0.31)	(0.32)	(0.32)	(0.32)	(0.33)	(0.32)
Business, Admin. & Law	0.10	0.14	0.16	0.20	0.21	0.18
	(0.30)	(0.34)	(0.37)	(0.40)	(0.41)	(0.38)
Arts & Humanities	0.16	0.16	0.16	0.17	0.18	0.17
	(0.37)	(0.37)	(0.37)	(0.37)	(0.38)	(0.37)
Education	0.02	0.04	0.02	0.02	0.02	0.02
	(0.14)	(0.19)	(0.14)	(0.12)	(0.13)	(0.14)
Nat. Sci., Maths & Stat.	0.25	0.23	0.21	0.18	0.17	0.20
	(0.43)	(0.42)	(0.40)	(0.38)	(0.37)	(0.40)
Veterinary & Agriculture	0.02	0.02	0.02	0.01	0.01	0.02
	(0.13)	(0.14)	(0.13)	(0.11)	(0.11)	(0.12)
Info & Comm. Tech.	0.01	0.02	0.05	0.08	0.10	0.06
	(0.07)	(0.15)	(0.21)	(0.27)	(0.29)	(0.23)
Engineering & Techn.	0.27	0.22	0.23	0.19	0.14	0.20
	(0.44)	(0.42)	(0.42)	(0.39)	(0.35)	(0.40)
Observations	22,430	50,073	62,923	80,820	34,192	250,438
Panel B: ***Earnings sample***						
Log real earnings	6.81	6.84	6.81	6.60	6.36	6.65
	(0.52)	(0.52)	(0.51)	(0.49)	(0.45)	(0.52)
Observations	2,870	9,270	14,061	19,015	7,396	52,612

Note: All statistics are weighted using person weights from the LFS. Standard deviations in parenthesis.

Table 2: Summary Statistics, by Decade of College Enrollment (Continued)

	Enrollment Decade					
	1960s	1970s	1980s	1990s	2000s	Total
Panel C: *Educational Achievements Sample*						
Number of GCSEs:						
1 or 2	0.01	0.01	0.01	0.03	0.02	0.02
	(0.11)	(0.10)	(0.12)	(0.16)	(0.15)	(0.14)
3 or 4	0.04	0.03	0.04	0.05	0.05	0.05
	(0.19)	(0.18)	(0.20)	(0.23)	(0.21)	(0.21)
5 to 7	0.33	0.31	0.27	0.27	0.20	0.26
	(0.47)	(0.46)	(0.45)	(0.44)	(0.40)	(0.44)
8 or more	0.62	0.65	0.67	0.65	0.73	0.67
	(0.49)	(0.48)	(0.47)	(0.48)	(0.45)	(0.47)
Observations	9,159	26,072	33,446	49,936	29,028	147,641
Degree Classification:						
Ordinary	0.14	0.13	0.10	0.05	0.05	0.08
	(0.35)	(0.34)	(0.30)	(0.23)	(0.21)	(0.27)
Third	0.11	0.09	0.06	0.06	0.04	0.06
	(0.32)	(0.29)	(0.25)	(0.23)	(0.20)	(0.24)
Lower Second	0.29	0.33	0.33	0.34	0.28	0.32
	(0.46)	(0.47)	(0.47)	(0.47)	(0.45)	(0.47)
Upper Second	0.35	0.35	0.41	0.45	0.49	0.43
	(0.48)	(0.48)	(0.49)	(0.50)	(0.50)	(0.50)
First	0.11	0.09	0.10	0.10	0.14	0.11
	(0.31)	(0.28)	(0.30)	(0.30)	(0.35)	(0.31)
Observations	8,675	25,018	32,823	51,193	31,234	148,943

Note: All statistics are weighted using person weights from the LFS. Standard deviations in parenthesis.

Table 3: Wages and Economic Conditions at Time of College Enrollment

	Outcome: Log real weekly wages					
	(1)	(2)	(3)	(4)	(5)	(6)
Unemp at enrollment	0.008	0.012	0.011	0.011	0.010	0.009
	(0.002)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.002)***
Age, age squared	Yes	Yes		Yes	Yes	Yes
Age Fixed Effects			Yes			
Calendar year FE	Yes	Yes	Yes	Yes	Yes	Yes
Trend in cohort effect		Yes	Yes	Yes + Fee Years	Yes	Yes
Race and nationality	Yes	Yes	Yes	Yes	Yes	Yes
Region of residence	Yes	Yes	Yes	Yes	Yes	
Cohorts included	All	All	All	All	1971–2004	All
Obs.	52,612	52,612	52,612	52,612	46,827	52,612
Nr. of Clusters	51	51	51	51	34	51
R^2	0.184	0.214	0.217	0.214	0.192	0.129

Note: ***, ** and * denote statistical significance at the one, five and ten percent levels, respectively. All regressions are weighted using person weights from the LFS. Standard errors are clustered by year of enrollment. The regressions use all observations for full-time workers with non-missing weekly wage data.

Table 4: Wages and Economic Conditions at Time of College Enrollment: Excluding Non-Standard Students

	Outcome: Log real weekly wages		
	(1)	(2)	(3)
Unemp at enrollment	0.013	0.012	0.014
	(0.002)***	(0.002)***	(0.002)***
Age, age squared	Yes	Yes	Yes
Calendar year FE	Yes	Yes	Yes
Trend in cohort effect	Yes		
Age at enrollment	18–19	18	19
Obs.	29,835	16,396	13,439
Nr. of Clusters	51	50	51
R^2	0.229	0.227	0.233

Note: ***, ** and * denote statistical significance at the one, five and ten percent levels, respectively. All regressions include a race dummy, a dummy for foreign nationals, and 19 region of residence dummies. All regressions are weighted using person weights from the LFS. Standard errors are clustered by year of enrollment. The regressions use observations for full-time workers with non-missing weekly wage data who enrolled into university at age 18 or 19.

Table 5: Labor Market Outcomes and Economic Conditions at Time of College Enrollment

	Log real wages		Pr(FT Employment)	
	(1)	(2)	(3)	(4)
Unemp at enrollment	0.028		0.002	0.001
	(0.005)***		(0.001)	(0.001)
Unemp at enrollment	-0.001			
$*$ Years since graduation	(0.0002)***			
Quartile of unemp.:				
2nd		0.025		
		(0.008)***		
3rd		0.067		
		(0.012)***		
4th		0.073		
		(0.008)***		
Age, age squared	Yes	Yes	Yes	Yes
Calendar year FE	Yes	Yes	Yes	Yes
Trend in cohort effect	Yes	Yes	Yes	Yes
Sample	Wages	Wages	Full	Full
Obs.	52,612	52,612	60,950	250,438
Nr. of Clusters	51	51	51	51
R^2	0.215	0.214	0.174	0.088

Note: ***, ** and * denote statistical significance at the one, five and ten percent levels, respectively. All regressions include a race dummy, a dummy for foreign nationals, and 19 region of residence dummies. All regressions are weighted using person weights from the LFS. Standard errors are clustered by year of enrollment. The dependent variable in Columns (1) and (2) is log real weekly wages. The dependent variable in Columns (3) and (4) is a dummy for full-time employment. Columns (1) and (2) use all observations for full-time workers with non-missing wage data. Column (3) uses the sample from Columns (1) and (2), plus all individuals interviewed during the same waves who are not working full time. Column (4) uses all observations from all waves, including all observations that are not part of the wage survey.

Table 6: Quantile Regressions of Log Real Wages on Economic Conditions at Time of College Enrollment

	Quantile								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Unemp at	0.003	0.009	0.012	0.013	0.013	0.013	0.015	0.017	0.013
enrollment	(0.00008)***	(0.00005)***	(0.00004)***	(0.00004)***	(0.00004)***	(0.00004)***	(0.00005)***	(0.00005)***	(0.00006)***
Obs.	52,612	52,612	52,612	52,612	52,612	52,612	52,612	52,612	52,612
Pseudo R^2	0.082	0.117	0.134	0.141	0.145	0.146	0.150	0.157	0.167

Note: ***, ** and * denote statistical significance at the one, five and ten percent levels, respectively. All regressions include calendar year fixed effects, a quadratic function of age, and a linear cohort trend, as well as a race dummy, a dummy for foreign nationals, and 19 region of residence dummies. All regressions are weighted using person weights from the LFS.

Table 7: Mechanisms

	Outcome: Log real weekly wages					
	(1)	(2)	(3)	(4)	(5)	(6)
Unemp at enrollment	0.008	0.010	0.009	0.008	0.009	0.009
	(0.002)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Unemp at graduation	-.037					
	(0.005)***					
Unemp at graduation	0.002					
∗ Years since graduation	(0.0002)***					
Age, age squared	Yes	Yes	Yes	Yes	Yes	Yes
Trend in cohort effect		Yes	Yes	Yes	Yes	Yes
Calendar year FE	Yes					
Field-specific year FE		Yes				
Occ-specific year FE			Yes			
Occ-field-specific year FE				Yes		
Ind-specific year FE					Yes	
Ind-field-specific year FE						Yes
Obs.	52,612	52,612	52,595	52,595	52,576	52,576
Nr. of Clusters	51	51	51	51	51	51
R^2	0.199	0.246	0.312	0.351	0.250	0.298

Note: ***, ** and * denote statistical significance at the one, five and ten percent levels, respectively. All regressions include a race dummy, a dummy for foreign nationals, and 19 region of residence dummies. All regressions are weighted using person weights from the LFS. Standard errors are clustered by year of enrollment. The occupation, industry, and field of study fixed effects are based on nine occupational categories, ten industries, and nine field of study groups, respectively.

Table 8: Academic Performance in High School

		Dummies for number of GCSEs			
	Continuous	1-2	3-4	5-7	8+
	(1)	(2)	(3)	(4)	(5)
Unemp at enrollment	-.020	0.0003	0.001	0.004	-.005
	(0.009)**	(0.0004)	(0.0005)**	(0.002)**	(0.002)**
Trend in cohort effect	Yes	Yes	Yes	Yes	Yes
Obs.	147,641	147,641	147,641	147,641	147,641
Nr. of Clusters	51	51	51	51	51
R^2	0.017	0.003	0.004	0.021	0.022

Note: ***, ** and * denote statistical significance at the one, five and ten percent levels, respectively. The dependent variable is based on the number of GCSE exams passed with a score of C or higher. This information is only collected starting in the final wave of 2005. Column (1) uses a continuous measure of the number of GCSEs passed, while the remaining columns use indicator variables for the corresponding intervals. All regressions include a race dummy, a dummy for foreign nationals, and 19 region of residence dummies. All regressions are weighted using person weights from the LFS. Standard errors are clustered by year of enrollment.

Table 9: Academic Performance in University

	Outcome: University degree class (continuous)				
	(1)	(2)	(3)	(4)	(5)
Unemp at enrollment	0.010	0.011	0.010	0.010	0.013
	(0.003)***	(0.003)***	(0.003)***	(0.003)***	(0.003)***
Trend in cohort effect	Yes	Yes	Yes	Yes	Yes
Age at graduation		Yes	Yes	Yes	Yes
Field of study FE			Yes	Yes	Yes
Field-specific cohort trend				Yes	Yes
GCSE-specific cohort trend					Yes
Obs.	148,943	148,943	148,943	148,943	135,564
Nr. of Clusters	51	51	51	51	51
R^2	0.045	0.045	0.057	0.059	0.067

Note: ***, ** and * denote statistical significance at the one, five and ten percent levels, respectively. The dependent variable is a continuous measure based on university degree class, with higher values corresponding to higher GPAs. All regressions include a race dummy, a dummy for foreign nationals, 19 region of residence dummies, and a quadratic cohort trend. All regressions are weighted using person weights from the LFS. Standard errors are clustered by year of enrollment. In Columns (1) to (4), the sample is restricted to individuals with information on their degree classification. In Column (5) the sample is restricted to individuals with information on the number of GCSE exams passed. This information is collected starting in the final wave of 2005.

Table 10: Degree class and wages

	Outcome: Log real weekly wages			
	(1)	(2)	(3)	(4)
Unemp at enrollment	0.008	0.008	0.008	0.008
	(0.002)***	(0.002)***	(0.002)***	(0.002)***
First Class		0.154		0.172
		(0.014)***		(0.014)***
Upper Second Class		0.076		0.112
		(0.015)***		(0.014)***
Lower Second Class		-.020		0.012
		(0.015)		(0.015)
Third Class		-.081		-.058
		(0.019)***		(0.017)***
Age, age squared	Yes	Yes	Yes	Yes
Calendar year FE	Yes	Yes		
Trend in cohort effect	Yes	Yes	Yes	Yes
Degree class-specific calendar year FE			Yes	
Field-specific calendar year FE				Yes
Obs.	30,241	30,241	30,241	30,241
Nr. of Clusters	51	51	51	51
R^2	0.218	0.232	0.234	0.263

Note: ***, ** and * denote statistical significance at the one, five and ten percent levels, respectively. All regressions include a race dummy, a dummy for foreign nationals, and 19 region of residence dummies. All regressions are weighted using person weights from the LFS. Standard errors are clustered by year of enrollment. In all columns, the sample is restricted to individuals with information on their degree classification. This information is only collected starting in the final wave of 2005.

Figure 1: UK Unemployment rate 1958-2016

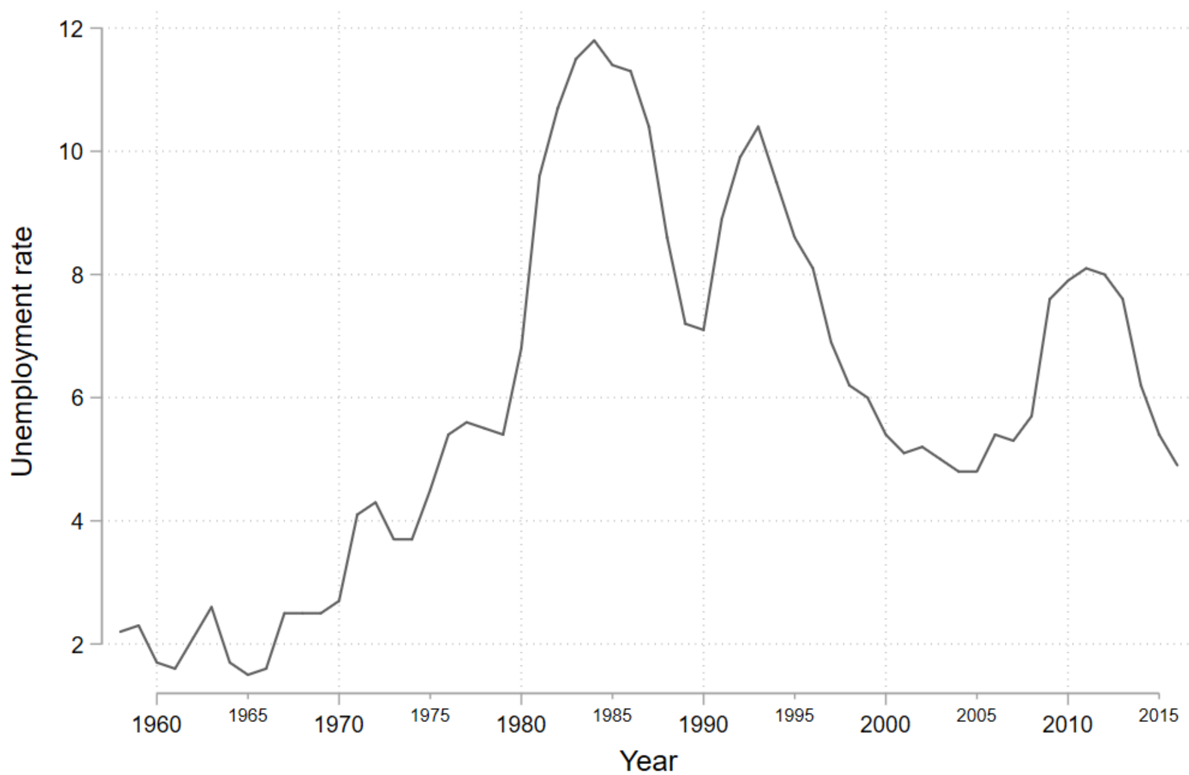
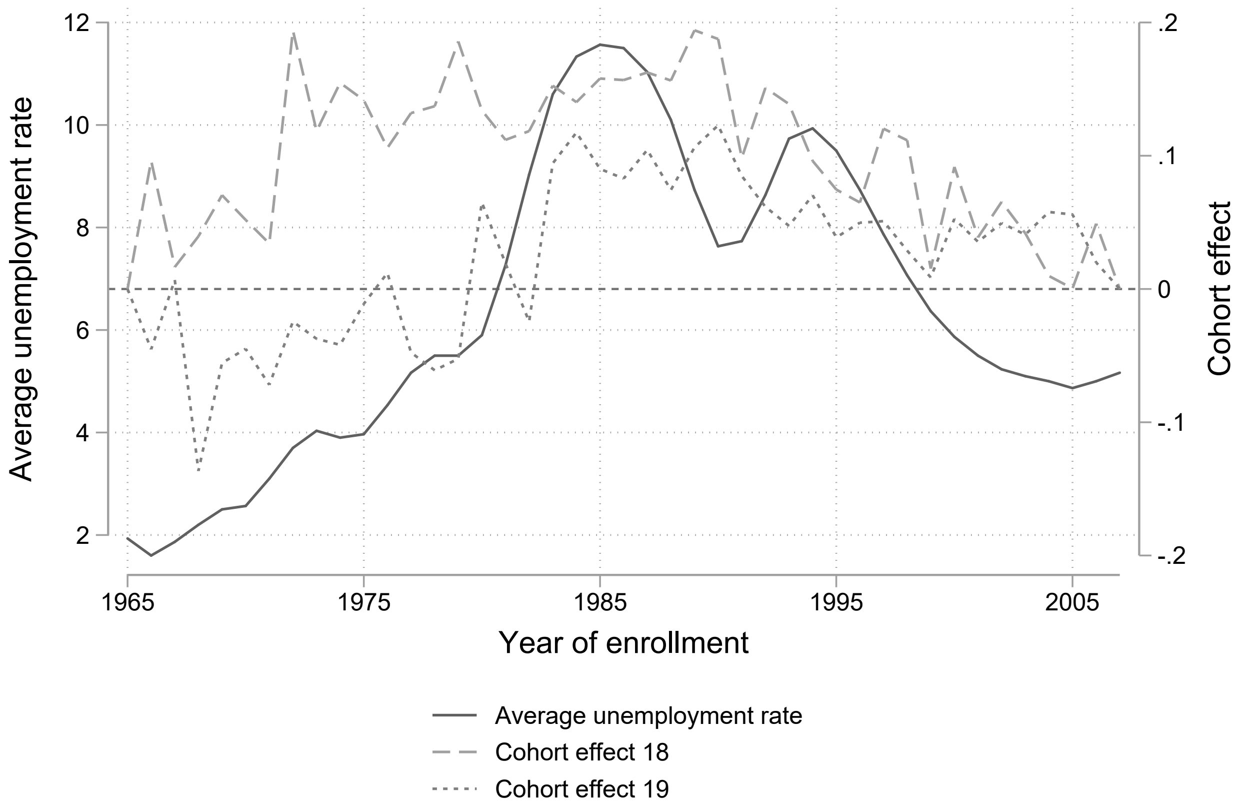
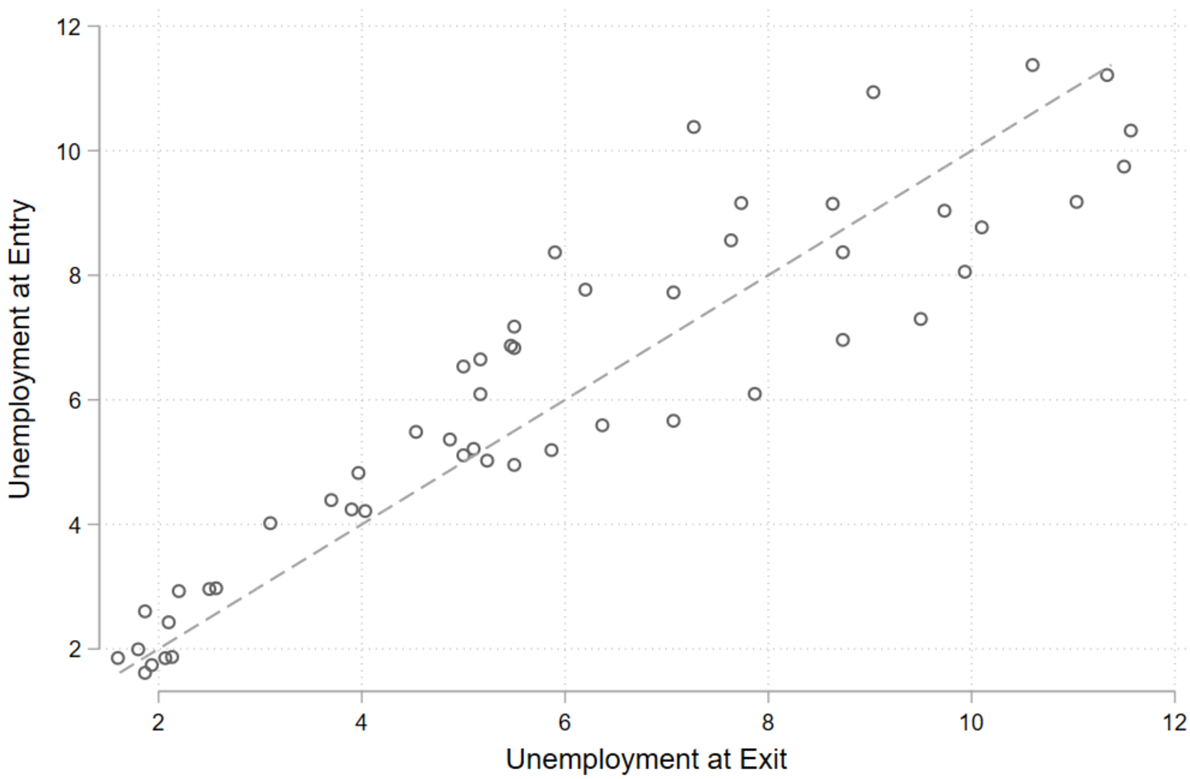


Figure 2: Detrended Cohort Effects in Wages. Age at Enrollment: 18 and 19



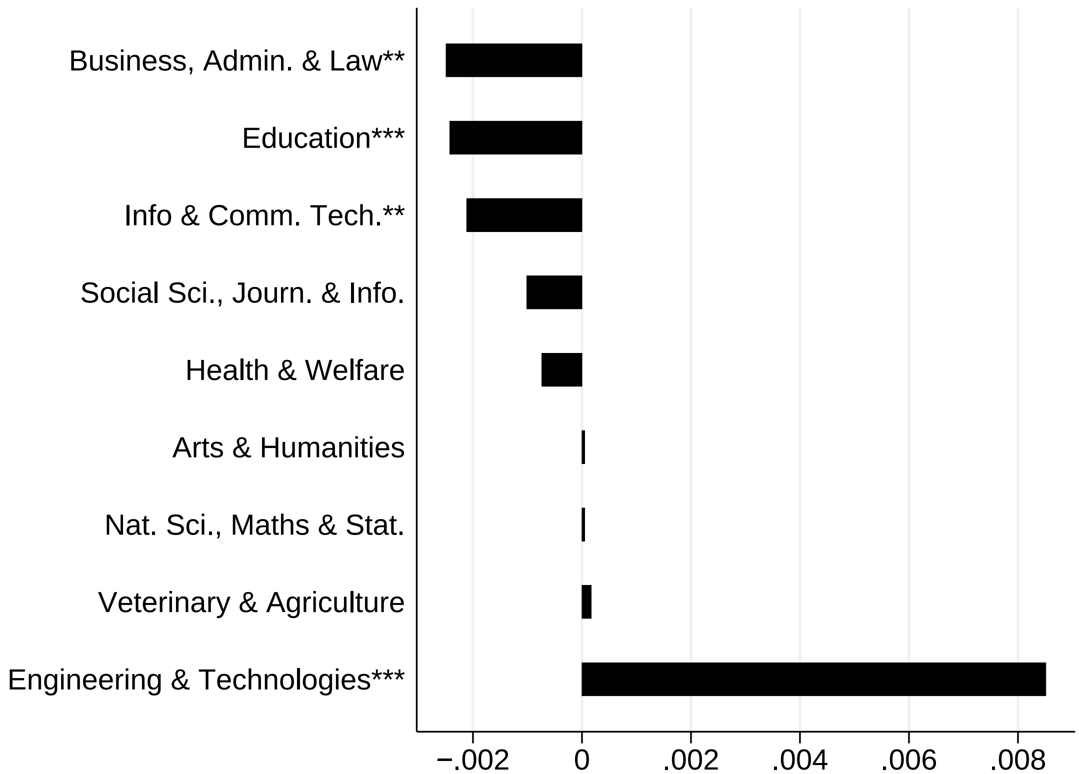
Note: The figure plots estimated cohort effects based on the Kwon et al. (2010) approach, where the first and last cohort effects are set to 0 and the estimates therefore represent deviations from a (non-identified) linear cohort trend. The line labeled "Cohort effect 18" is based on an estimation which uses only individuals who enroll at age 18, while the line labeled "Cohort effect 19" is based on an estimation which uses only individuals who enroll at age 19. The estimated effects are based on regressions of log real weekly earnings which include a full set of age and calendar year fixed effects, a race dummy, a dummy for foreign nationals, and 19 region of residence dummies. The regressions are weighted using person weights from the LFS, and they use all observations for full-time workers with non-missing weekly wage data who enroll at the relevant age. Due to limited sample size when restricting to specific enrollment ages, we exclude cohorts who enrolled before 1965 or after 2007 for this part of the analysis.

Figure 3: Unemployment Rates at the Time of College Enrollment and College Graduation, by Cohort



Note: Each dot represents a cohort defined by the enrollment year in college. The y-axis indicates the unemployment rate at college entry, and the x-axis the unemployment rate at the time of college graduation.

Figure 4: Change in major selection probabilities



Note: Bars represent the estimated coefficients for the effect of unemployment rate at college entry on the probability of selecting each of the nine major categories. ***, ** and * denote statistical significance at the one, five and ten percent levels, respectively. Regressions are based on 250,518 observations, and include controls for race, nationality and a quadratic cohort trend. All regressions are weighted using person weights from the LFS. Standard errors are clustered by year of enrollment.

Appendix Tables

Table A.1: Wages and Economic Conditions at Time of College Enrollment: Scotland Adjustment

	Outcome: Log real weekly wages					
	All	Excl. Scot	All	Excl. Scot	All	Excl. Scot
	(1)	(2)	(3)	(4)	(5)	(6)
Unemp at enrollment	0.008	0.008	0.011	0.011	0.010	0.011
	(0.002)***	(0.002)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Age, age squared	Yes	Yes	Yes	Yes		
Age Fixed Effects					Yes	Yes
Calendar year FE	Yes	Yes	Yes	Yes	Yes	Yes
Trend in cohort effect			Yes	Yes	Yes	Yes
Obs.	45,254	41,218	45,254	41,218	45,254	41,218
R^2	0.181	0.183	0.213	0.213	0.216	0.216

Note: ***, ** and * denote statistical significance at the one, five and ten percent levels, respectively. All regressions include a race dummy, a dummy for foreign nationals, and 19 region of residence dummies. All regressions are weighted using person weights from the LFS. Standard errors are clustered by year of enrollment. The regressions use observations for male full-time workers with non-missing wage data for the waves from 2001 onwards (which is the period for which we have information on location of birth). Columns (2), (4) and (6) exclude individuals who were born in Scotland.

Table A.2: Wage Regressions by Field of Study

	(1)	(2)	(3)	(4)	(5)
Field-specific Coeff on Unemp at Enrollment					
Health & Welfare	0.002	-0.001	-0.002	Base	-0.003
Social Sciences, Journalism & Info	0.001	0.006	0.006*	0.007	0.002
Business, Admin & Law	0.006	0.007**	0.007**	0.009	0.004
Arts & Humanities	0.001	0.006***	0.007***	0.008	0.004
Education	0.003	0.012***	0.009**	0.013*	0.012**
Nat Sci, Math & Stat	0.008***	0.015***	0.015***	0.016***	0.011***
Veterinary & Agriculture	0.016	0.020*	0.020*	0.021*	0.016
Info & Comm Tech	0.024***	0.020***	0.019***	0.022***	0.022***
Engineering & Technologies	0.007**	0.011***	0.010***	0.012*	0.007**
Field-specific age profile (quadratic)	Yes	Yes	Yes	Yes	Yes
Field-specific calendar year FE	Yes	Yes	Yes	Yes	Yes
Overall trend in cohort effect		Yes			
Field-specific trend in cohort effect			Yes		
Cohort dummies				Yes	
Field-specific scarring effects					Yes
Obs.	52,612	52,612	52,612	52,612	52,612
R^2	0.217	0.249	0.250	0.251	0.235

Note: ***, ** and * denote statistical significance at the one, five and ten percent levels, respectively. The dependent variable is log real weekly wages. All regressions include a race dummy, a dummy for foreign nationals, and 19 region of residence dummies. All regressions are weighted using person weights from the LFS. Standard errors are clustered by year of enrollment.

Table A.3: University Degree Class Probability

	Ordinary	Third	Lower Second	Upper Second	First
	(1)	(2)	(3)	(4)	(5)
Unemp at enrollment	0.0006	-.003	-.002	0.002	0.003
	(0.001)	(0.0007)***	(0.002)	(0.002)	(0.001)***
Obs.	148,943	148,943	148,943	148,943	148,943
R^2	0.104	0.022	0.025	0.025	0.018

Note: ***, ** and * denote statistical significance at the one, five and ten percent levels, respectively. The dependent variables are indicator variables for the degree class obtained at university. This information is only collected starting in the final wave of 2005. All regressions include a quadratic overall cohort trend, a full set of field-of-study-specific linear cohort trends, a control for age at graduation, a race dummy, a dummy for foreign nationals, and 19 region of residence dummies. All regressions are weighted using person weights from the LFS. Standard errors are clustered by year of enrollment.

Table A.4: Probability of non-employment during full time college studies

	(1)	(2)	(3)
Avg. Unemp.	0.022	0.016	0.017
	(0.005)***	(0.005)***	(0.005)***
Age Fixed Effects	Yes	Yes	Yes
GCSE Dummies		Yes	Yes
GCSE $\times$ Age			Yes
Obs.	50,593	32,153	32,153
R^2	0.070	0.066	0.070

Note: ***, ** and * denote statistical significance at the one, five and ten percent levels, respectively. The dependent variable is an indicator variable for non-employment at the time of the survey. Avg. Unemp. is a measure of the current unemployment rate, computed as the average of the unemployment rate in the year of the survey and in the previous two years. The sample is restricted to male full-time students. All regressions include a race dummy, a dummy for foreign nationals, and 19 region of residence dummies, as well as a full set of age fixed effects, a quadratic time trend and an age specific linear time trend. All regressions are weighted using person weights from the LFS. Standard errors are clustered by year. Columns (2) and (3) further restrict the sample to individuals with information on their GCSE score; this information is only collected starting in the final wave of 2005. Column (2) includes four GCSE performance group dummies, while Columns (3) adds an age-specific GCSE group trend.