Careers and Mismatch for College Graduates: College and Non-college Jobs

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Andrew Agopsowicz, Chris Robinson, Ralph Stinebrickner and Todd Stinebrickner

Working Paper # 2017-4 **July 2017**

Centre for Human Capital and Productivity (CHCP)

Working Paper Series

Department of Economics
Social Science Centre
Western University
London, Ontario, N6A 5C2
Canada

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Andrew Agopsowicz **Chris Robinson** **Ralph Stinebrickner**

Todd Stinebrickner

University of Western Ontario

April 25, 2017

Abstract

A large literature studies the wage consequences of over-education" in the sense of a worker, by some measure, having a higher level of education than is required for the job. We use unique new data to reexamine the common interpretation that initial over-education represents a harmful type of mismatch that arises due to information induced frictions. We contrast this with the alternative that college graduates are heterogeneous with respect to their human capital and that the labor market is appropriately allocating them to jobs, even when many are observed starting in jobs that do not require a college degree.

*This work was supported by the Mellon Foundation, the Spencer Foundation, the National Science Foundation, the Centre for Human Capital and Productivity at the University of Western Ontario and by the Canadian Social Sciences and Humanities Research Council.

1 Introduction

There is a large literature that studies the wage consequences of "over-education" in the sense of a worker, by some measure, having a higher level of education than is required for the job. Recently there is an increasing concern with college graduates taking "non-college jobs" and pushing high school graduates out of the labor market altogether.[1] The standard interpretation in the over-education literature and in recent debates is to consider the substantial amount of over-education observed in initial post-college jobs as a mismatch between the worker and the job, with the presumption being that workers who are initially mismatched will have substantially worse outcomes over the lifecycle than other identically qualified individuals. For example, Baert, Cockx and Verhaest (2013) describe over-education as a "trap". In this paper we use unique new data to reexamine the common interpretation that initial over-education represents a harmful type of mismatch that arises due to information induced frictions. We contrast this with the alternative that the labor market is doing a relatively good job allocating workers even when many college graduates are observed entering the labor force in jobs that do not require a college degree.

Initial over-education is problematic if workers with college degrees suffer substantial life-cycle wage losses when they start in jobs that do not require a college degree. However, establishing whether this is the case versus the alternative that there exists a variety of career paths into which heterogeneous college graduates may be appropriately allocated is a difficult task, requiring a comparison of the life-cycle earnings of workers who start in college jobs with the life-cycle earnings of workers with the same skills and abilities (i.e., the same human capital) who start in non-college jobs.

Our project is made possible by access to detailed data about workers and jobs that we collected specifically to address the challenges that have traditionally been present when making this kind of comparison. The Berea Panel Study (BPS), described in Section 2 and used previously to study an extensive number of outcomes and decisions during school, is a longitudinal study that has followed two cohorts of college students from the time they entered college past the age of thirty.[2] With respect to the need to hold worker skills and abilities constant when making life-cycle comparisons, the data must be comprehensive enough to permit some assessment of whether college graduates

[1] The over-education literature is surveyed in Hartog (2000). A recent paper that studies college graduates taking non-college jobs is Beaudry, Green and Sand (2016).

[2] Previous studies using the BPS include Stinebrickner and Stinebrickner (2008, 2012, 2014).

who are never observed in a job that requires a college degree are similar to individuals who have received jobs that require college degrees, suggesting some form of mismatch, or are more similar to above average non-college graduates, consistent with individuals being appropriately allocated. Administrative data in the BPS contain detailed information about well-recognized human capital proxies such as college grade point average and college major. Detailed longitudinal data about jobs comes from annual post-graduation surveys. Perhaps most fundamental for this project is yearly wage data and data that characterizes the education required for one's job. With respect to the latter, a branch of past research has recognized the value of survey questions that elicit this information directly from the worker, but the BPS contains the first longitudinal information of this type.

The BPS data also include some other types of unique information that are useful for obtaining a deeper understanding of issues related to over-education. For example, a policymaker may not be overly concerned about differences in earnings across similar workers if apparent mismatch arises because preferences over types of work lead some students to knowingly choose college majors where over-education and lower pay are likely to be present. The BPS includes detailed data describing beliefs about earnings in different majors and preferences towards the types of work associated with different majors. As a second example, recent literature suggests that observing the tasks that the worker performs on the job is potentially valuable for delving deeper into the channels by which over-education potentially influences earnings. The BPS contains the first longitudinal data of this type.

In Section 3 we describe the measure of required education that we use in our paper and relate it to others used previously in the literature. Looking at initial jobs we find that, consistent with recent public discourse, roughly 40% of the college graduates in our sample begin their careers in jobs that do not require a college degree - "non-college jobs." We begin our investigation of mismatch by viewing the sample as a homogenous group of workers with a college degree, but take advantage of our longitudinal data to examine whether concerns about mismatch based on initial over-education are alleviated when we view the path of required education and the path of wages over a longer interval. Roughly speaking, concerns would be alleviated if individuals who start in non-college jobs do not suffer substantial wage losses over the life-cycle. The longitudinal nature of our data would be helpful for uncovering this possibility if it could provide evidence that: 1) even if non-college jobs are an undesirable part of one's career, workers tend to transition very quickly to college jobs or 2) many good careers (i.e., careers with high lifetime earnings) involve workers initially spending some time in jobs that are also performed by some workers without a college degree. With respect to 1), we find evidence that some workers tend to transition very quickly to college jobs, but that a considerable number of workers take a non-trivial number of years to transition to a college job or do not transition to a college job at any point during the sample period. With respect to 2), we find that individuals who never transition to a college job have substantially lower wages over the first eight years of their careers than students who start in a college job. As for the group of students who start in non-college jobs but transition to a college job at some point, they begin their careers with substantially lower wages than students who start in a college job. While the wage gap between the two groups does narrow significantly over time, the group that starts in a non-college job receives significantly lower total earnings over the first eight years in the workforce.

Thus, viewing the sample as a homogenous group of workers with a college degree, the fact that students who start in non-college jobs receive lower wages over the sample period would lead to a conclusion that mismatch is a problem. The objective of this paper is to shed some light on whether this is the correct conclusion. A key feature explored in the paper is the role of important aspects of worker heterogeneity that are not observed in traditional data sources.

In Section 4 we recognize that, even within a single school, the assumption that college graduates are homogeneous with respect to human capital is likely to be problematic. Previous research has recognized that college GPA is a natural proxy for taking into account heterogeneity in human capital at the time of labor market entrance. We find that low GPA graduates are much more likely to never hold a college job than high GPA graduates. The fact that the market seemingly views the low GPA group as having lower human capital than the high GPA group raises the possibility that some college graduates with low GPA may be more similar to above average non-graduates than to good college graduates. This implies that, from a conceptual standpoint, it is difficult to understand the importance of mismatch from observing low GPA graduates in non-college jobs; these students may simply have been appropriately allocated to "overlap" jobs that could be held by either college or non-college graduates.

Given the relevance of worker heterogeneity in an evaluation of the importance of mismatch, we focus primarily on high GPA students. This is consistent with our objective of examining whether, because of the potential importance of worker heterogeneity, over-education should not automatically be equated with problematic mismatch. Because high GPA students will tend to be least similar to non-graduates, a finding that starting careers in non-college jobs leads to significant life-cycle wage losses for this group in particular would seem to be indicative of problematic mismatch. We find little evidence of this. Consistent with the notion that some good careers begin in non-college jobs, high GPA graduates who start in non-college jobs but transition to college jobs do not suffer wage losses relative to high GPA graduates who start in college jobs. To provide some support for this notion, we take advantage of innovative job task measures in the BPS to examine how the evolution of the time allocation to job tasks at different levels is related to different career paths. We find that, despite having wages that are similar to high GPA graduates who start in college jobs, high GPA graduates in the transition group begin their careers in jobs involving work that is similar to that of high GPA graduates who never hold a college job before eventually transitioning to jobs involving work that is similar to that of high GPA graduates who start in college jobs.

Given the wage pattern found for the high GPA graduates who start in non-college jobs but transition to college jobs, the only remaining high GPA subgroup for which mismatch might be problematic is the subgroup that never holds a college job. However, we find that only 15.6% of high GPA college graduates fit this description. Further, we find evidence of other important differences in human capital between this subgroup and other high GPA students. Namely, high GPA graduates who never hold a college job are overwhelmingly in low paying majors, especially humanities. In addition, taking advantage of expectations and preference data, we find strong evidence that these students intentionally chose to forego higher earnings because of preferences over types of work. Thus, overall, our analysis uncovers little evidence of mismatch for the high GPA group.

Section 5 involves a brief examination of the low GPA group. Because some students in this group may be similar to above average non-graduates, it is difficult to make conclusive statements about the importance of mismatch from observing that a non-trivial number of students in this group are allocated to non-college jobs. However, we attempt to reinforce a primary conclusion in the paper - that taking into account heterogeneity in human capital is crucial when one thinks about whether observed overeducation represents mismatch - by examining whether we can identify any differences in human capital between low GPA graduates who begin their careers in college jobs and low GPA graduates who begin their careers in non-college jobs. We find that low GPA graduates who are observed in “college job” careers are much more frequently from professional majors. We discuss why it might be relevant that these majors differ from other majors in requiring some form of a common credential.

Some conclusions are presented in Section 6.

2 The Berea Panel Study

The Berea Panel Study (BPS) is a longitudinal survey that was initiated by Todd and Ralph Stinebrickner to provide detailed information about the college and early post-college periods. The project involves surveying students who entered Berea College in the fall of 2000 and the fall of 2001 approximately sixty times from the time they entered college through 2014. In this paper, we focus on the early work period for individuals who graduated, by taking advantage of post-college surveys that were collected annually after students left school. More than ninety percent of all graduates in the two entering BPS cohorts completed one or more of these annual surveys, and the response rate on the these surveys remained above eighty percent for most of the sample period. Five hundred fifty-three individuals completed at least one post-graduation survey, and we typically use as large a subset of this full sample as possible after taking into account missing data.[3] The survey data are merged with administrative records from Berea College that provide demographic characteristics and the academic measures that serve as our proxies for human capital.

It is necessary to be appropriately cautious about the exact extent to which the results from our case study would generalize to other demographic groups or to other specific institutions.[4] However, there are important benefits of studying one school. The most obvious benefit is that the study of one school played a crucial role in making our collection of detailed data feasible. However, several other benefits arise related to the need to hold human capital constant across workers when comparing labor market outcomes and related to the need to accurately measure the education that is needed for one's job. With respect to the former: 1) the study of one school makes standard proxies for human capital such as college grade point average and college major directly comparable across workers and 2) holding school quality constant across workers removes the general concern that workers who

[3]Most of the graduates that completed at least one post-graduation survey completed multiple surveys and can be followed from job to job. For example, two thirds of the 553 individuals that completed at least one post-graduation survey completed at least six surveys in their first eight years after graduation. See Appendix Table A1 for a full description of the distribution of responses.

[4]However, important for the notion that the basic lessons from our work are pertinent for thinking about what takes place elsewhere, Berea operates under a standard liberal arts curriculum, and the students at Berea are similar in academic quality to, for example, students at the University of Kentucky (Stinebrickner and Stinebrickner (2008)). In addition, in earlier work we found that academic decisions at Berea look very similar to decisions made elsewhere. For example, dropout rates are similar to those found elsewhere (for students from similar income backgrounds) and patterns of major choice and major-switching at Berea are similar in spirit to those found in the NLSY by Arcidiacono (2004).

do not receive college jobs may simply be from lower quality colleges and, therefore, have lower human capital. With respect to the latter, because a worker's views about whether a college degree is needed for his job will depend on the quality of his degree, holding school quality constant across workers may be beneficial for making our self-reported measures of required education comparable across respondents.[5]

Past policy discussion, which involves a stated concern that many college graduates do not initially obtain college jobs, characterizes initial jobs using a simple dichotomy for these jobs ("college" or "non-college"). However, the recent literature on job skills and tasks includes an analysis of the response of workers to changes in "task" prices that can shift the allocation of workers of a given education level into different tasks.[6] In this approach, the idea of a simple dichotomy between "college jobs" and "non-college" jobs gives way to more of a continuum, where some jobs are almost exclusively done by either college graduates or non-college graduates, but others involve a mix of college and non-college graduates who are more marginal in their respective groups and more similar to one another. It is not necessarily a mismatch to observe a college graduate in a job that is also performed by non-college graduates, given heterogeneity in the task capabilities within college and non-college graduates. What is relevant for mismatch is the task capabilities or human capital of the worker relative to the particular job.

Given the discussion in the previous paragraph, Berea College seems to be a reasonable type of school for our case study. All college graduates tend to be viewed identically in policy discussion. However, there is undoubtedly heterogeneity in the human capital of college graduates. Some college graduates may be quite similar to above average non-graduates. The argument in this paper is that to get a better understanding of possible mismatch and its consequences, it is necessary to take into account that not all college graduates or college jobs are the same. The BPS allows a study of allocation to "college" and "non-college" jobs where there may be a significant fraction of graduates that overlap, in terms of human capital, with above average non-graduates. In contrast, graduates

[5]Our motivation for studying one school is similar in spirit to that in, for example, Bertrand *et al.* (2010) who examine the earnings of a sample of MBA graduates from one top business school.

[6]At a given set of task prices, given heterogeneity within education group in how good workers are at producing the tasks, college graduates will be distributed across jobs in a way that is different from non-college graduates, but in many "overlap" jobs there will be both college and non-college graduates. That is, some jobs may be done almost exclusively by college graduates, and some almost exclusively by non-college graduates, but other jobs will be done by both. Moreover, at different task prices the distributions will change so that some jobs that were mainly done by college graduates could become jobs that are done by non-college graduates, or vice-versa. See, for example, Acemoglu and Autor (2011), Beaudry, Green and Sand (2016).

from the most selective elite universities may be almost exclusively in the upper tail of the continuum of college graduates where there is no overlap with above average non-graduates.

3 College and Non-College Jobs: Definitions, Basic Statistics, and Life-cycle Wages

In this paper we first follow the traditional literature in using a simple dichotomous measure for "college" and "non-college" jobs. We then add to this some measures of heterogeneity within college graduates and in career paths in order to understand whether the observed pattern of some college graduates in jobs also performed by non-college graduates is a true mismatch or is better understood as an appropriate allocation of heterogeneous workers on a continuum of college and non-college jobs.

3.1 Defining College and Non-college Jobs

For a worker whose education level is observed, characterizing whether mismatch exists involves obtaining the required level of education for the worker's observed job. Hartog (2000) groups the measures of required schooling that have been used in the literature into three types, *job analysis (JA)*, *realized matches (RM)*, and *worker self-assessment (WA)*, based on the source of information. In *JA*, the level of education for a job is typically obtained from a data source such as the *Dictionary of Occupations (DOT)* by aggregating analysts' evaluations of required education over all jobs in the same occupation. In *RM*, a measure of required education is derived for a job from observations on the levels of education of other workers in the same occupation, using, for example, the mean or mode of the distribution of workers in the occupation. Finally, in *WA*, the worker answers a survey question related to the schooling required for the job. The question varies from survey to survey. The question in the *Panel Study of Income Dynamics (PSID)* used in Sicherman (1991) is: "How much formal education is required to get a job like yours?"

We use a *WA* type indicator for whether or not a college degree is required for the job that a worker holds in a particular year. The indicator is derived from the answer to the question: "*What type of degree is needed for your job(s)*".[7] From the standpoint of obtaining as accurate a view as possible about the education needed for the actual job that a person holds, this type of question has the strong appeal that it refers specifically to the worker's actual job. In this respect, *JA* measures,

[7] There are three possible answers: "*no degree needed*", "*degree - any area*" and "*degree - my area.*" Our indicator of whether a college degree is needed takes a value of one if a person circles either of the last two categories.

which must be assigned to a worker's job on the basis of the worker's occupation (rather than the worker's actual job), are at a substantial disadvantage given the large amount of variation in job tasks that has recently been found to exist even within detailed occupation codes.[8] The same disadvantage is present for *RM* measures, which are also based on a worker's occupation; a worker may be in an occupation where the mean education level is below a college degree but the (often large) variation within the occupation could lead to a case where as many as half of the jobs in the occupation do require a college degree.

Naturally, there are costs and benefits of each method. Perhaps the biggest concern about *WA* approaches is that different workers may have different views about whether a particular job requires a college degree. However, our study of one school may help mitigate this concern, at least to the extent that this type of inconsistency arises because views about whether a particular job requires a college degree depend on the quality of one's degree. Further, having required education assessed by individual workers may be particularly appealing given the longitudinal focus of our work. This project represents the first time that a longitudinal *WA* measure has been available. Then, when using our longitudinal data to examine transitions between non-college and college jobs, our required education indicator takes advantage of an assessment by the same person over time.[9]

3.2 College and Non-college jobs: Basic Patterns

Policy discussion has often been motivated by evidence that many college graduates begin their careers in jobs for which they are overeducated. For example, survey evidence from 2013 finds that about 40% of college graduates began their careers in jobs that do not require a college degree.[10]

The first panel of Table 1 provides a basic description of the responses to our required education

[8] Robinson (forthcoming) Table 1 compares the variation within and across three digit occupations using an occupation distance measure based on the DOT job characteristics; Autor and Handel (2013) use individual level worker skill data collected under the *Princeton Data Improvement Initiative* to document a large variation in job level skills within occupation. Bowlus, Mori and Robinson (2016) document substantial variation in job characteristics by age within occupation. The need to assign *JA* measures and *RM* measures on the basis of an occupation code (rather than an actual job) arises because standard longitudinal surveys contain occupation codes but do not typically contain detailed job descriptions.

[9] Strong evidence of the importance of having consistent evaluations across time is provided in Kambourov and Manovskii (2008) who show that retrospective coding of a worker's entire occupation history by a single coder reduced the number of occupation switches by half compared to the original data where occupations were evaluated by different coders each year.

[10] https://newsroom.accenture.com/subjects/accenture-corporate/four-out-of-10-recent-college-grads-are-underemployed-new-accenture-research-finds.htm and https://www.insidehighered.com/quicktakes/2015/05/14/survey-49-recent-grads-say-theyre-underemployed

	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8
Fraction College Jobs	0.59	0.65	0.69	0.69	0.71	0.74	0.73	0.78
N	333	364	368	360	372	352	344	300
Hourly Wages ($2005)								
Mean Wage - College	13.13	13.75	15.35	16.05	16.63	17.87	18.29	19.37
Standard Deviation	(4.60)	(4.95)	(6.46)	(6.73)	(7.65)	(8.81)	(8.85)	(9.70)
N	190	228	249	247	261	259	243	227
Mean Wage - Non College	9.50	10.74	11.16	12.17	12.90	12.86	13.11	13.33
Standard Deviation	(3.04)	(4.46)	(4.01)	(5.74)	(5.86)	(5.97)	(6.75)	(6.95)
N	131	128	111	106	100	88	93	65

Table 1: College and Non-College Jobs: Basic Statistics

question in the BPS for all individuals employed at a job with 30 or more hours.[11] The first entry in the first column shows that, consistent with the type of percentages that have motivated policy discussion, 41% of all workers in our sample begin their careers in a job that does not require a college degree. Wage information is shown in the second panel. The wage information in the first column reveals the underlying reason for potential concern about mismatch; on average, workers in non-college jobs in year 1 after graduation earn only 72% as much as those in college jobs ($9.50 vs. $13.13).

3.3 Life-cycle Wages and College/Non-college Job Careers

Relative to samples of college graduates that would be obtained from general longitudinal surveys, our sample is undoubtedly quite homogeneous - since all students have been exposed to identical college quality and all have been admitted and chosen to attend the same school. In this section, we treat the full sample as a homogenous group of workers with a college degree and examine whether potential concerns about initial over-education may be alleviated when we take advantage of the longitudinal aspect of our data to examine what happens after the first year. Considering a longer term perspective, do individuals who start in non-college jobs suffer substantial wage losses over the life-cycle?

One way in which substantial life-cycle wage losses may be avoided is that, even if non-college jobs are an undesirable part of one's career as suggested by the year 1 evidence in Table 1, workers

[11]The total observations up to and including year 8 range from 333 to 372. The number of observations varies with years since graduation due to some individual-time observations being missing in the data, or because the individual was not employed in the year or was employed at a job that has less than 30 hours.

may transition very quickly to college jobs.[12] We examine this for the sample as a whole by taking advantage of our longitudinal access to the required education question. We do find evidence that some workers tend to transition very quickly to college jobs. For example, the first panel of Table 1 shows that, by year three, the fraction of Berea College graduates in non-college jobs has fallen by almost twenty-five percent from 41% to 31%. Nonetheless, the fact that this percentage falls even further by the end of the period (to 22% by year 8) but still remains substantially greater than zero indicates that a considerable number of workers either take a non-trivial number of years to transition to a college job or do not transition to a college job at any point during the sample period.

A second possible reason why substantial life-cycle wage losses may be avoided is that many good careers (i.e., careers with high lifetime earnings) may involve a worker initially spending a number of years working and learning in jobs that are also performed by workers without a college degree. This type of explanation may seem most appealing in cases where the worker eventually transitions to a college job. For example, perhaps a worker must have some knowledge of the shop floor before becoming a manager at the factory. This motivates us to examine lifetime wage differences after dividing the sample into a discrete number of career groups based on each respondent's job history. Specifically, we abstract from much of the complexity present in the raw job history data by stratifying the sample into four groups that are designed to capture the general types of job history patterns of interest: (1) those that start and end in a college job (CC); (2) those that start in a non-college job and transition into a college job (NC); (3) those that start and end in a non-college job (NN); and (4) those that start in a college job and transition into a non-college job (CN). Assignment to the groups is based on whether the respondent has an "early" college or non-college job at the beginning of the history and a "late" college or non-college job at the end of the history. While this ignores details of complex transitions that might be important in theory between the early and late jobs types, we find that complex transitions are not very prevalent in practice.[13]

Starting with our full sample of 553 workers, the requirement that an observation is needed early and late in the job history reduces the total sample size to 512. To focus on individuals who are not continuing their formal education, we add a full-time work requirement of 30 hours per week,

[12]This possibility is the focus of Clark *et al* (2016) who use a RM measure.

[13]For the CC group, all job observations between the early job and the late job are college jobs for 93% of the individuals. For the NC group, almost all (97%) have a single transition from a non-college job to a college job between the early and late job. For a large majority (72%) of the NN group, all job observations between the early job and the late job are non-college jobs. The precise assignment rules for the groups are detailed in the Appendix, section A1.

which reduces our sample to 394 workers. The distribution of career paths for this sample is given in Table 2. The fraction in the *CC* (always college) group is 56%, followed by 22% in the *NN* (always

Job History Group	Frequency	Percent
CC	221	56.09
NN	86	21.83
NC	59	14.97
CN	28	7.11
Total	394	100

Table 2: Distribution of Career Types Among Respondents

non-college) group and 15% in the *NC* (transition to college) group. The remaining *CN* (transition from college to non-college) group is the smallest at 7%. The analysis in the paper largely abstracts from the *CN* group, given the small sample size. However, this group is very similar to the *NN* group in both observed characteristics and behavior.

Figure 1 plots the average log hourly wages by years since graduation for the three largest groups, *CC*, *NC*, and *NN*. The *NN* and *CC* groups have very different profiles. As would be expected given

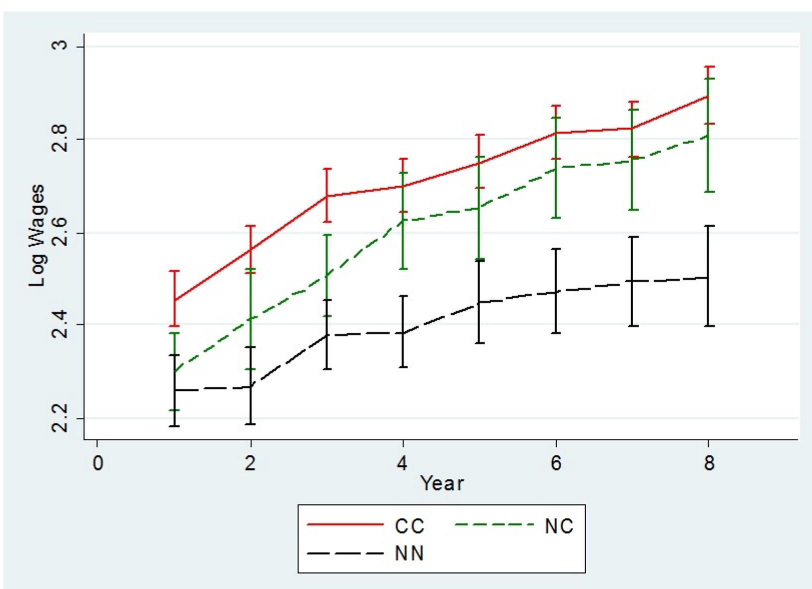

Figure 1: Log Real Hourly Wages by Career Type

the lower panel of Table 1, in the first year after graduation there is a strongly significant gap between the *CC* and *NN* groups of 19.5 log points, which grows to 31.5 log points by year 4 and 39 log points by year 8. It is harder to know from Table 1 what to expect for a comparison of the *NC* and *CC* groups. Figure 1 shows that *NC* starts similarly to the *NN* group with a gap of 15.4 log points behind the *CC* group, but by year 4 this gap closes to only 7.6 log points.[14] Nonetheless, while the gap does narrow, in the sample there remains a gap by the end of the sample period and the total area between the *CC* and *NC* lines implies that individuals in the *NC* group have non-trivially smaller total earnings over their first years in the labor market.

Thus, viewing individuals in the *NN*, *NC*, and *CC* groups as homogeneous college graduates with identical human capital, one would reasonably conclude that mismatch is a problem. The *NN* group appears to be permanently mismatched, with big wage losses over the life-cycle. The *NC* group appears to be at least temporarily mismatched at the beginning of their careers, with non-trivial wage losses in aggregate over the first eight years. However, even within this school, the assumption that individuals have similar human capital is likely to be problematic. In the next section we examine whether conclusions about the importance of mismatch change when we take advantage of our detailed measures of human capital to explore the extent to which wages differences across the groups in Figure 1 arise because of differences in human capital rather than from, for example, frictions that result in some workers not finding appropriate initial matches.

4 High GPA College Graduates: Is There Evidence of Mismatch?

Section 3 found that significant lifetime earnings differences exist between those who start their careers in jobs that require a college degree and those that start their careers in jobs that are not exclusively held by college graduates. Is this mismatch or do workers who start in non-college jobs simply have lower levels of human capital than workers who start in college jobs, making them close to above average non-college graduates? As discussed in the Introduction, observing low GPA graduates in career paths other than the *CC* group with relatively low earnings provides little evidence of significant mismatch if, in terms of human capital, the low GPA graduates are close to above average non-college graduates. However, high GPA graduates provide a group that, in terms

[14] In Figure 1 the 95% confidence intervals at each year for the *CC* and *NC* groups overlap. However, estimates from standard parametric log wage regressions show strong statistically significant differences between all three groups. For example, regressing log wages on dummy variables for the *CC* and *NC* career types and a quadratic in years since graduation, with *NN* as the omitted group, yields a coefficient on *CC* of 0.308 with a standard error of 0.019, and a coefficient on *NC* of 0.198 with a standard error of 0.026.

of human capital, should be different from above average non-college graduates so that, within the high GPA group, lower life-cycle earnings for graduates outside the CC group would constitute stronger evidence of mismatch. In this section we therefore focus on college graduates with high levels of human capital as measured by the student's cumulative college grade point average (GPA).

4.1 GPA and Allocation to Career Types

If Berea College graduates are homogeneous in terms of human capital and allocation to the career types, CC, NC and NN, occurs simply through frictions, there should be no relation between GPA and the likelihood of being in any career type. Alternatively, if the labor market allocates college graduates to career types based on their human capital, at least in part, rather than through frictions, we should expect to see a relationship between GPA and career type. We find that a high GPA strongly affects the probability of being in the CC group. Table 3 shows the joint distribution of the dichotomous GPA variable and career type. The probability of a below average GPA ("low" GPA) Berea graduate being observed in the CC group is 0.4560. The probability for an above average GPA ("high" GPA) graduate is over 40% higher at 0.6509 and the difference is highly statistically significant. Conversely, a below average GPA Berea graduate has close to a 30% probability of being observed in the NN group, while the probability for a high GPA graduate is only half of this.

GPA	CC	NC	NN	CN	Total
High	138	28	33	13	212
Low	83	31	53	15	182
Total	221	59	86	28	394

Table 3: Joint Distribution of Career Type and GPA

Overall, the evidence suggests that human capital heterogeneity among the Berea college graduates, as measured by their GPA, is important for their allocation to their career type. Given this important heterogeneity, we revisit the evidence presented in Figure 1 that treated all the graduates as homogeneous in terms of their human capital and examine instead the wage patterns across the first eight years of the working life-cycle for the high (above average) GPA graduates.

4.2 Life-cycle Wages for High GPA graduates

Figure 2 plots the average hourly wages by years since graduation for the high (i.e., above average) GPA graduates in the three groups.[15] The difference between the results in Figure 1 and the results

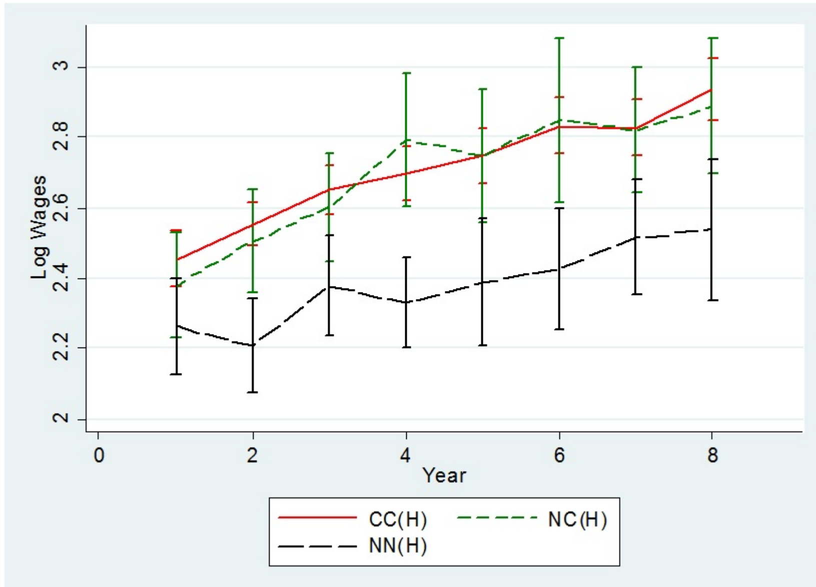

Figure 2: Log Real Hourly Wages by Career Type: High GPA

in Figure 2 show the importance of controlling for "ability" even within a single college of a given "quality." Comparing the high GPA *CC* group, *CC(H)*, with the high GPA *NC* group, *NC(H)*, we find no evidence in Figure 2 that those who transition to college jobs after starting in non-college jobs have lower earnings over the first eight years than those that are always in college jobs. Thus for high GPA graduates, there is no evidence that individuals with a career path that ends with a college job but begins with some non-college job experience should be viewed as having been mismatched. Thus the results are consistent with the $NC(H)$ group being appropriately allocated despite the fact that they start their careers in non-college jobs.[16] Repeating an earlier example, perhaps in some careers a worker needs to acquire knowledge of the shop floor in a learning-by-doing manner before becoming a manager at the factory.

We take advantage of unique task data in the BPS to further explore the appeal of this potential

[15]The mean GPA in the pooled sample of the four groups is 3.1; using a lower cutoff for "high" GPA graduates would introduce some college graduates into the sample that may be similar to above average non-college graduates.

[16]Figure 2 imposes no parametric time trend and reports expected log wages for each year. Alternative parametric treatment of time in the regression yields similar results to the linear trend in terms of the differences between the groups. The NN group is the omitted career type dummy variable. This reproduces the results from Figure 2 showing that for above average GPA graduates there are no significant differences between the CC and NC groups. The F-statistic, F(1,1238), for a test of equality of the coefficients for CC and NC is 0.49 with a P-value of 0.484, showing no significant difference between the CC and NC groups, as plotted in Figure 2.

interpretation. Empirical evidence consistent with this interpretation would come from observing that, despite having wages that are similar to the *CC(H)* group in all years, individuals in the *NC(H)* group tend to begin their careers in jobs involving work that is similar to that of individuals in the *NN(H)* group, but eventually transition to jobs involving work that is similar to that of individuals in the *CC(H)* group. The task data are described in detail in Appendix section A.4. The data are unique in allowing us to compute the percentage of time that is spent on four different subtasks that can be ranked by task level, within each of three general task categories: interaction with People, Information and Objects.

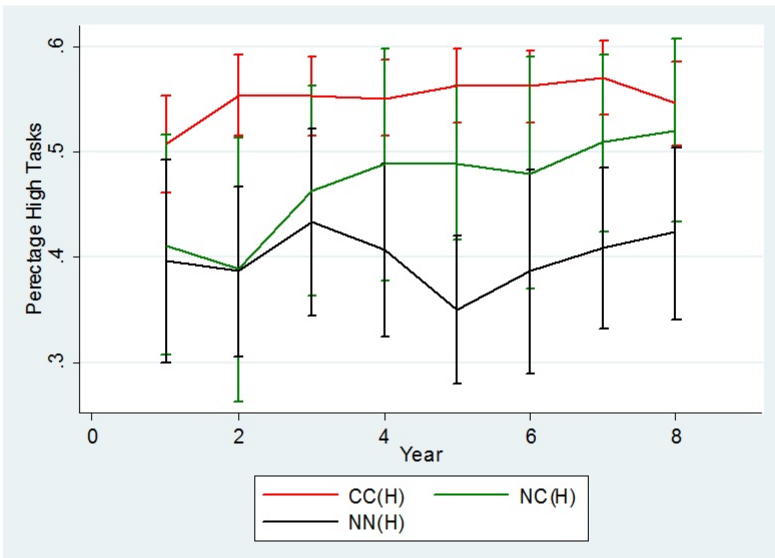

Figure 3: Fraction of Time Spent on High Level Tasks

Figure 3 shows the mean amount of time that is spent on "high skilled tasks" in each year for the three high GPA career groups, *CC(H), NC(H)*, and *NN(H)*, where "high skilled tasks" are the two highest-skilled sub-tasks in each of three general task categories (People, Information, and Objects). Consistent with the interpretation described above, we find that individuals in the *NC(H)* group begin their careers by performing the same amount of high skilled tasks as individuals in the *NN(H)* group, but eventually transition to jobs in which they perform similar amounts of high skilled tasks as individuals in the *CC(H)* group.

Figure 3 combines the People, Information and Objects task categories. Breaking this down into

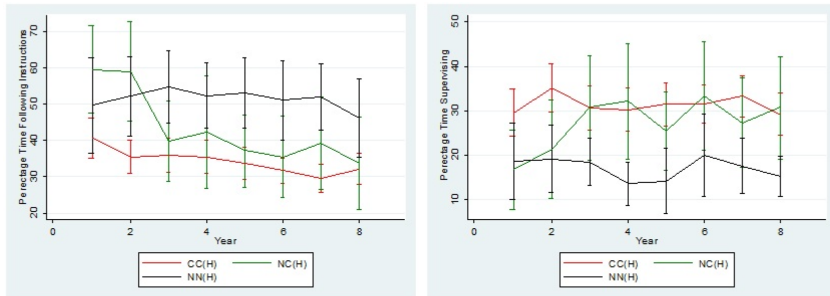

Figure 4: Time Spent Following Instructions and Supervising

the component task categories, the pattern in Figure 3 occurs primarily because of the People and Information tasks. This is the case because Objects tasks are not particularly important for college graduates, regardless of whether or not they have college jobs.[17] Motivated by the importance of interpersonal interactions in our example - where a worker needs time on a shop floor before becoming a manager - Figure 4 shows patterns for the high level People subtask "supervising" and the low level People subtask "following instructions". Consistent with the example, the results show a substantial change in People tasks for the $NC(H)$ group over time relative to the $CC(H)$ group, despite the fact that Figure 2 showed that the relative wages of the groups do not change.

4.3 Majors, Earnings and Allocation to Career Types

Given the similarity of the wage profile of the *NC(H)* group to the *CC(H)* group, the main concern about mismatch for the high GPA group would have to come from the *NN(H)* group. At first glance, the evidence in Figure 2 suggests that some concern is potentially warranted because individuals in this group have substantially lower average log wage trajectories than the *CC(H)* and *NC(H)* groups. However, it is worth stressing that, because of the strong role of GPA in allocating graduates to college jobs, this group accounts for only 15.6% of high GPA graduates (Table 3).

Further, because Figure 2 takes into account only a single, somewhat coarse proxy for human capital, differences between the $NN(H)$ group and the other high GPA groups cannot immediately be viewed as evidence of mismatch. As such, concerns about mismatch for the high GPA group could be further alleviated by finding additional differences between the groups. One possibility is

[17]A full description of the time allocation and importance by task and task level is given in Table A4 in the Appendix. The object related high skill tasks only account for a small fraction of time for the BPS sample.

that the dichotomous GPA measure leaves important differences in GPA unaccounted for across the high GPA groups. We do find that the mean GPA conditional on having a high GPA is lowest in the sample for the *NN* group. However, the difference in mean GPA between the *NN(H)* group and the other groups is small, suggesting that the incompleteness of our GPA measure is, at most, only a partial explanation for the lower earnings of the students in *NN(H)*.[18] This motivates us to explore a prominent non-GPA source of potential differences in human capital for the $NN(H)$ group relative to the other high GPA graduates - their choice of college major.

Recent research has studied human capital heterogeneity as reflected in different college majors. There is evidence that some human capital is major specific and that substantial differences in earnings exist across college majors. Table 4, which reports real wages averaged over all years, shows that large differences by major also exist in the BPS data. Consistent with what has been documented using other data sets in the literature, earnings are highest for those majoring in Science, Professional programs, and Business. The lowest earnings are for graduates majoring in Education, Agriculture and Humanities. While high GPA graduates earn more in general, the pattern for earnings differences across majors holds both for the full sample, and separately for the sample of high GPA graduates. Thus, choice of major will affect earnings even within high GPA graduates.

Providing support for the notion that the lower earnings of the $NN(H)$ group may not represent mismatch because differences in human capital may remain between the the three career groups in Figure 2, Appendix Table A.2 shows important differences in the representation of the majors by career groups. Importantly, the $NN(H)$ group that experiences the low earnings in Figure 2 is made up largely of graduates from the low earnings majors: Agriculture, Education and Humanities. Humanities graduates alone make up over half of the $NN(H)$ group and almost three quarters of the $NN(H)$ group are from the three low earnings majors. By contrast, the $CC(H)$ and $NC(H)$ groups have much less representation from the low earnings majors.[19] For example, Humanities graduates make up only 21% of the combined $NC(H)$ and $CC(H)$ groups.

One way of viewing this pattern is that some majors are much more heavily represented in the "overlap" jobs that are done by both college graduates and non-college graduates, and that these majors pay less in the labor market in all jobs, whether college jobs or not. The importance of college

[18]The mean GPA for high GPA students in the *NN* group is 3.443 compared to 3.452, 3.488 and 3.510 in the *CN, NC* and *CC* groups, respectively.

[19]Full details on the distribution of majors by career group for high and low GPA are given in Table A2 in the Appendix.

Major	Full Sample		High GPA Sample	
	Average Wage	N	Average Wage	N
Agriculture	12.78	231	12.69	98
	(.376)		(.613)	
Business	16.32	448	17.48	243
	(.324)		(.476)	
Education	12.35	258	12.62	154
	(.240)		(.341)	
Humanities	13.46	609	13.47	413
	(.242)		(.305)	
Science	17.89	391	19.72	261
	(.585)		(.822)	
Professional	16.89	616	18.79	255
	(.334)		(.594)	
Social Science	14.74	319	16.14	161
	(.392)		(.701)	

Notes: Standard errors in parentheses

Table 4: Real Wages by Major

major choice can be seen in the fact that it plays as important a role in allocating college graduates to career types as GPA. To see this, the estimated joint effects of GPA and college major choice on the probability of being in the career types CC and NC, from a linear probability model are reported in Table 5. In the first column, Humanities is the omitted major and results are reported for the whole sample. Relative to Humanities graduates, graduates in all other majors have a substantially larger probability of being in the "college career" group CC, and the difference is statistically significant for all but Agriculture. The result from Table 3 that a college graduate with a high GPA is much more likely to be in the CC group remains after controlling for major. For example, the probability of a Humanities major being in CC is roughly twice as high for a high GPA graduate than for a low GPA graduate. In terms of magnitudes, the negative effect of choosing the Humanities major is as large as the positive effect of having a high GPA. This is shown more directly in the second column which reports the results from an alternative linear probability model that includes only dummy variables for high GPA and Humanities. The positive effect on the probability of a high GPA (0.2189) is totally offset by the negative effect of choosing the Humanities major (-0.2386).

The remaining columns show that the allocative importance of major remains within the high GPA group. Again, there are generally strong differences by major and in particular there is a strong negative effect for Humanities relative to other majors. The final column shows the probability of

Major	Pr(CC)		Pr(CC|High GPA)		Pr(CC or NC|High GPA)	
Agriculture	.1420	-	.1654	-	.1090	-
	(.1014)		(.1419)		(.1209)	
Business	.1929	-	.3167	-	.3167	-
	(.0808)		(.1037)		(.0884)	
Education	.1931	-	.2643	-	.2262	-
	(.0944)		(.1176)		(.1002)	
Science	.3255	-	.3887	-	.3522	-
	(.0854)		(.1026)		(.0874)	
Professional	.2765	-	.2357	-	.2738	-
	(.0734)		(.0986)		(.0841)	
Social Science	.2193	-	.2318	-	.2803	-
	(.0871)		(.1156)		(.0985)	
Humanities	-	-.2368	-	-.2803	-	-.2785
		(.0577)		(.0704)		(.0601)
High GPA	.2149	.2189	-	-	-	-
	(.0494)	(.0488)				
Constant	.2649	.4991	.4500	.7306	.5833	.8618
	(.0598)	(.0369)	(.0599)	(.0375)	(.0510)	(.0320)
N	393	393	212	212	212	212

Notes: Standard errors in parentheses

Table 5: College Career Probability by Major

a high GPA graduate being observed in one of the two career groups, CC or NC, that showed significantly higher earnings relative to the NN group (Figure 2). The probability is 0.86 for non-Humanities majors, but is reduced to only 0.58 for Humanities majors.

Overall, a choice of major such as Humanities, which is very common for graduates in the *NN(H)* group, has two consequences: it lowers the probability of being in the CC career path, even for high GPA graduates, and it results in lower earnings.

4.4 Expectations of Earnings and Enjoyment: High GPA graduates

The previous section found that important differences in college major exist between individuals in the $NN(H)$ group and those in the $CC(H)$ and $NC(H)$ groups. If college major is simply viewed as a second proxy for human capital in the same vein as GPA, then these wage-influencing differences in major would help alleviate concerns that differences in earnings between the $NN(H)$ group and the other groups represent problematic mismatch. However, even if college major is viewed somewhat different conceptually than GPA, concerns about mismatch would tend to be alleviated if the lower earnings of the $NN(H)$ group can be viewed as arising from informed choices about major driven by preferences about types of work. We take advantage of unique expectations data to examine this possibility.

At multiple times during school, each individual reported the mean of the distribution describing her beliefs about future earnings for each of several particular major groups that could be chosen and reported how enjoyable she would expect to find the types of jobs she would receive if she had that particular major. The first panel of Table 6 reports the sample averages of these expectations for the high GPA humanities graduates in the NN group. The expected income (at age 28) is reported in \$1000s. The enjoyment rating is on a four point scale from (1) "very enjoyable" to (4) "very unenjoyable".[20] We see strong evidence that, at the time they chose their major, individuals were aware that a major in humanities would lead to substantially lower income. For example, on average, humanities majors anticipated that their earnings in Humanities would be 22% lower than their earnings in Science (\$28,230 vs. \$36,000), 28% lower than their earnings in Business (\$28,230 vs. \$39,380), and 20% lower than their earnings in Professional degrees (\$28,230 vs. \$35,080). The enjoyment ratings provide striking evidence about why students chose these majors, even when earnings were expected to be low. For example, 75% of students thought that a job in Humanities would be very enjoyable. In contrast, only 18% of students thought a job in Science would be very enjoyable, only 8% of students thought a job in Business would be very enjoyable, and only 8% of students thought a job in a professional area would be very enjoyable. Similarly, only 8% of students thought Humanities would be unenjoyable, while these percentages are 55%, 33%, and 42% for Science, Business, and Professional.[21]

Another interesting feature of Table 6 is that the high GPA humanities graduates in the *CC(H)* group expect to earn more (at age 28) than those in the *NN(H)* group. They expect to earn 10% more in Humanities related jobs, over 20% more in Science related jobs, and 26% more in Professional related jobs. This is consistent with the higher mean GPA for the high GPA students in the CC(H) group compared to the $NN(H)$ group reported earlier. However, the difference in mean GPAs is relatively small (3.510 vs. 3.443) and remains small (3.581 vs. 3.459) if the sample is restricted to

[20] See the Appendix for more details on the questions and the preamble to the questions.

[21] The expected income and enjoyment patterns were re-estimated by taking individual differences of the other majors compared to humanities for each individual and estimating the mean differences to provide direct tests of the statistical significance of the differences in both expected income and enjoyment. The expected income and enjoyment differences are all highly statistically significant.

	Expected Income ($1000s)	Enjoyment Category Distribution			
		very enjoyable	somewhat enjoyable	somewhat unenjoyable	very unenjoyable
Career Type: Non-college Jobs ($NN(H)$)					
Humanities	28.23	.750	.167	.000	.083
	(1.80)				
Science	36.00	.182	.091	.182	.546
	(2.75)				
Business	39.38	.083	.250	.333	.333
	(2.41)				
Professional	35.08	.083	.250	.250	.417
	(1.98)				
Career Type: College Jobs ($CC(H)$)					
Humanities	31.09	.909	.046	.000	.046
	(1.54)				
Science	43.27	.000	.191	.286	.524
	(2.75)				
Business	39.86	.000	.191	.571	.238
	(2.62)				
Professional	44.14	.095	.429	.381	.095
	(3.86)				

Notes: Standard errors in parentheses

Table 6: Expected Income and Enjoyment of Humanities Graduates by Major

humanities graduates. The data on expected incomes, recorded well before most of the respondents started looking for jobs, suggest that there may be some additional human capital differences between high GPA humanities graduates observed in the college jobs career group, $CC(H)$, and those in the non-college jobs career group, $NN(H)$.

5 Low GPA College Graduates: Heterogeneity, Overlap Jobs or Mismatch?

Section 4 uncovers little evidence of significant mismatch for high GPA graduates, especially taking into account the choice of college major. Our motivation for making this group the primary focus of our analysis is that, in terms of human capital, high GPA graduates should tend to have relatively little overlap with non-college graduates. In contrast, low GPA graduates potentially overlap significantly with some of the better non-college graduates. As such, it is hard to make conclusive statements about the importance of mismatch from observing that some students in this group are allocated to college jobs while others are allocated to non-college jobs. Nonetheless, in an effort to reinforce a primary conclusion in the paper - that taking into account heterogeneity in human capital is crucial when one thinks about whether observed overeducation represents mismatch - in this section we examine whether we can identify any types of differences in human capital between low GPA graduates who begin their careers in college jobs and low GPA graduates who begin their careers in non-college jobs.

Figure 5 compares the profiles of the low GPA graduates in each of the career groups. As in Figure 2, the NN group has significantly lower wages than the CC group. By contrast, in Figure 5 the low GPA transition group, $NC(L)$, starts out significantly lower than the always college group $CC(L)$, at the same level as the $NN(L)$ group. The wages of the transition group do increase faster than those of the $CC(L)$ group, especially after period 2, but overall the $CC(L)$ group still does better. Can we identify any differences in human capital that can explain why the $CC(L)$ group does better than the $NC(L)$ group and the $NN(L)$ group?

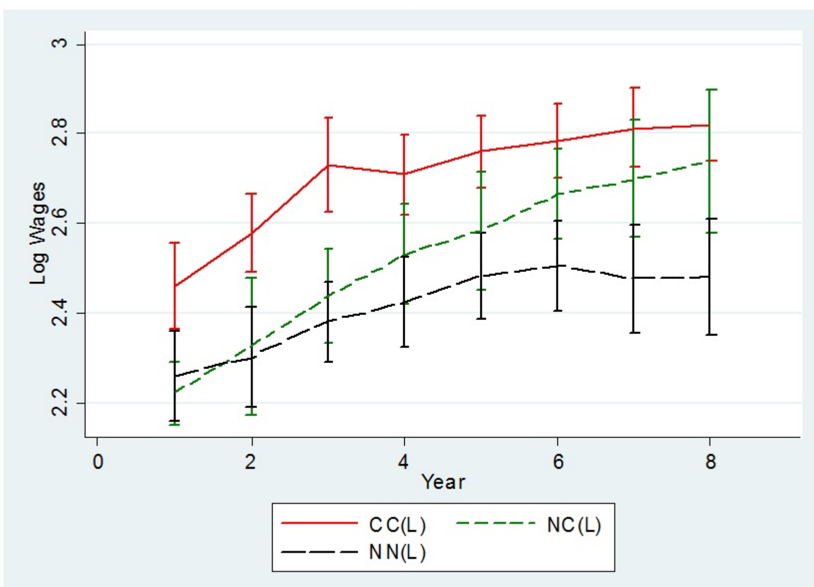

Figure 5: Log Real Hourly Wages by Career Type: Low GPA

The analysis of the previous section suggests that a large part of the wage difference between NN(H) and the the other high GPA groups, CC(H) and NC(H), can be attributed to different representation in high and low paying majors (as well as additional sources of lower unobserved human capital for high GPA graduates in the NN group). Here we examine whether differences in major might exist between the CC(L) group and the other low GPA groups, NC(L) and NN(L).

As seen in Appendix Table A.2, we do find substantial differences in major across groups. For example, the percentage of individuals who have a Professional major is 50% higher for the $CC(L)$ group than for the combined $NC(L)$ and $NN(L)$ group. In addition, the percentage of individuals who have a Humanities major is only half as big for the $CC(L)$ group as it is for the combined $NC(L)$ and $NN(L)$ group. This implies that there are three Professional majors for every Humanities major in the $CC(L)$ group, but that the number of Professional majors and Humanities majors are equal in the combined $NC(L)$ and $NN(L)$ group.

Table 5 showed that high GPA Humanities majors have a lower probability of being in the CC group than high GPA students in other majors. Table 7 shows that low GPA Humanities majors have lower probabilities of being in the CC group than low GPA students in the Professional major. The estimates for other majors have the same sign but are statistically insignificant.

Major	Pr(CC|Low GPA)
Agriculture	.0892 (.1500)
Business	.0346 (.1296)
Education	.0774 (.1563)
Science	.2068 (.1500)
Professional	.2693 (.1141)
Social Science	.1774 (.1351)
constant	.3226 (.0893)

Note: Robust standard errors in parentheses

Table 7: Probability of Career Type CC by Major for Low GPA

In terms of why Professional majors are more likely to appear in the $CC(L)$ group than the other low GPA groups, Professional jobs often require a credential which tends to be obtained as part of a Professional degree program. Graduates in these jobs will therefore report that the job requires a college degree. That is, Professional jobs will be done exclusively by college graduates so respondents in these jobs will report the job as a college job. By contrast there may be more overlap in the college and non-college make up of jobs done by graduates from majors that do not provide a credential. The existence of credentials may also shed light on why low GPA students tend to have fairly successful wage outcomes when they have Professional degrees. Overall, Professional degrees tend to pay well

(Table 4), and the presence of a credential may help low GPA professional students, who obtain the credential, pool with higher GPA professional students during the application process. Over time the variation in human capital within a given credential is likely to be revealed. This is consistent with the observation that the $CC(L)$ group starts with earnings as high as the $CC(H)$ group, but they experience lower subsequent earnings growth in comparison to the high GPA students in either the $CC(H)$ group or the $NC(H)$ group.

6 Conclusion

From a conceptual standpoint, taking into account heterogeneity in human capital is important when considering issues related to over-education. Understanding whether over-education represents problematic mismatch requires a comparison of the life-cycle earnings of workers who start in college jobs with the life-cycle earnings of workers with the same human capital who start in non-college jobs. Previous research has recognized that college GPA is a natural proxy for taking into account heterogeneity in human capital at the time of labor market entrance. We find that low GPA graduates are much more likely to never hold a college job than high GPA graduates. The fact that the market views the low GPA group as having lower human capital than the high GPA group raises the possibility that some college graduates with low GPA may be more similar to above average non-graduates than to good college graduates. This implies that, while observing low GPA graduates in non-college jobs could be indicative of a mismatch, these students may simply have been appropriately allocated to "overlap" jobs that could be held by either college or non-college graduates. By contrast, observing high GPA graduates in non-college jobs provides a stronger case for mismatch rather than appropriate allocation based on relatively low levels of human capital. Our analysis, therefore, focused on the high GPA group.

We highlight situations where, without access to our college GPA and college major proxies for human capital, we would incorrectly conclude that over-education represents problematic mismatch. As one example, for the sample as a whole, starting in a non-college job leads to a loss in lifetime earnings for workers who transition at some point to a college job. However, we find no evidence of this loss in lifetime earnings when we consider the more homogeneous subset of the sample that has above average college GPAs. As another example, even among students with above average college GPAs, some individuals never work in a college job during the sample period and receive low wages.

However, we find that this group is overwhelmingly from low earning college majors, especially Humanities. In addition, taking advantage of expectations and preference data, we find strong evidence that these students intentionally chose to forego higher earnings because of preferences over types of work.

It is not our goal to dismiss the possibility that over-education may sometimes be problematic. This would not be a reasonable objective for a variety of reasons, including the reality that our analysis is made possible by the study of one school. However, our paper provides a strong warning that, because of the fundamental importance of taking into account heterogeneity in workers, over-education should not automatically be equated with problematic mismatch. This warning is important because information characterizing heterogeneity may not always be present in the types of data that are readily available to policymakers.

References

[1] Daron Acemoglu and David Autor. Skills, Tasks and Technologies: Implications for Employment and Earnings. In Orley C. Ashenfelter and David Card, editors, *Handbook of Labor Economics*. North Holland, 2011.

[2] David Autor and Michael Handel. Putting Tasks to the Test: Human Capital, Job Tasks and Wages. *Journal of Labor Economics*, 31:S59–96, 2013.

[3] Stijn Baert, Bart Cockx, and Dieter Verhaest. Overeducation at the start of the career: Stepping stone or trap? *Labour Economics*, 25:123–140, 2013.

[4] Paul Beaudry, David Green, and Benjamin Sand. The Great Reversal in the Demand for Skill and Cognitive Tasks. *Journal of Labor Economics*, 34:S199–S247, 2016.

[5] Marianne Bertrand, Claudia Goldin, and Lawrence Katz. Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors. *American Economic Journal: Applied Economics*, 2:228–255, 2010.

[6] Audra Bowlus, Hiroaki Mori, and Chris Robinson. Ageing and Skill Portfolios: Evidence from Job Based Skill Measures. *Journal of the Economics of Ageing*, 7:89–103, 2016.

[7] Brian Clark, Clement Joubert, and Arnaud Maurel. The Career Prospects of Overeducated Americans. NBER Working Paper No. 20167, 2016.

[8] J. Hartog. Over-education and earnings: where are we, where should we go? *Economics of Education Review*, 19:131–147, 2000.

[9] Gueorgui Kambourov and Iourii Manovskii. Rising Occupational and Industry Mobility in the United States: 1968-1997. *International Economic Review*, 49:41–79, 2008.

[10] Chris Robinson. Occupational Mobility, Occupation Distance and Specific Human Capital. *Journal of Human Resources*, forthcoming.

[11] N. Sicherman. Overeducation in the Labor Market. *Journal of Labor Economics*, 9:101–122, 1991.

[12] N. Sicherman and O. Galor. A Theory of Career Mobility. *Journal of Political Economy*, 98:169–192, 1990.

[13] Ralph Stinebrickner and Todd Stinebrickner. The Effect of Credit Constraints on the College Drop-Out Decision: A Direct Approach Using a New Panel Study. *American Economic Review*, 98:2163–2184, 2008.

[14] Ralph Stinebrickner and Todd Stinebrickner. A Major in Science? Initial Beliefs and Final Outcomes for College Major and Dropout. *The Review of Economic Studies*, 81:426–472, 2014.

[15] Todd Stinebrickner and Ralph Stinebrickner. Learning about Academic Ability and the College Dropout Decision. *Journal of Labor Economics*, 30:707–748, 2012.

[16] Jennifer Yuen. Job-education match and mismatch: Wage differentials. *Statistics Canada: Perspectives*, pages 16–26, 2010. Catalogue no. 75-001-X.

A Appendix

A.1 Careers and Response Rates for the Post Graduation Surveys Sample

Jobs data are constructed from post graduation surveys of two cohorts of graduates from Berea College, one graduating in 2000 and the other in 2001. Observations on college or non-college jobs at two points in time or more in the first 8 years after graduation are available for a total of 513 respondents. Approximately two thirds of these had at least 6 out of the first 8 surveys with valid job observations. Assigning respondents to the four career types requires at least one job observation with at least 30 hours a week at the start of the post-college job career and at least one in the later phase. The observation for the "start" job is the job in the second post-graduation survey if available; if this is not available it is substituted with the job in the first graduation survey; finally, if this is not available it is substituted with the job in the third observation survey. The observation for the "end" job is the job in the seventh post-graduation survey if available; if this is not available it is substituted with the job in the sixth graduation survey; finally, if this is not available it is substituted with the job in the eighth observation survey. There are 394 respondents for which these conditions are satisfied.

The valid response rates for the post-graduation surveys varies from year to year. The fractions in the four career types, *CC, NC, NN* and *CN* in the observed sample for each year are given in Table A1. In principle, these fractions should be constant over years since graduation since the status is permanently assigned based on the whole history. However, for the same reason as there

	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8
Fraction CC	0.57	0.57	0.56	0.57	0.57	0.59	0.56	0.56
Fraction NC	0.14	0.13	0.15	0.13	0.15	0.12	0.15	0.16
Fraction CN	0.06	0.07	0.08	0.08	0.06	0.07	0.07	0.08
Fraction NN	0.22	0.22	0.21	0.21	0.22	0.22	0.21	0.21
N	286	311	319	302	322	329	322	277

Table A1: Career Types by Year

is variation in the number of observations with years since graduation, there is a slight variation in the observed fractions in Table A1.

A.2 Distribution of Major by Career Type and GPA

The detailed distribution of Major by Career type is given in the following table.

	Agr	Bus	Edu	Hum	Sci	Pro	Soc
CC(H)	8	23	15	27	26	24	15
NC(H)	1	4	2	8	3	6	4
NN(H)	3	2	4	17	1	4	2
CN(H)	1	1	0	8	1	1	1
CC(L)	7	10	6	10	9	29	12
NC(L)	2	3	3	6	4	6	6
NN(L)	7	11	3	13	4	12	3
CN(L)	1	4	3	2	0	2	3

Table A2: Distribution of Major by Career Type and GPA

A.3 Expectations Data in the BPS

A.3.1 Description

The preamble to the question used to elicit the expectations data is as follows:

> We realize that you may or may not be sure right now exactly what area of study you will graduate with. In the first column below are listed possible areas of study....In the fourth column write down the yearly income you would expect to earn at age 28 (or 10 years from now if you are now 20 years of age or older) if you graduated with each of these areas of study. In the fifth column, write down how interesting you find each particular area of study. In this column enter a number 1-5 where 1=extremely interested, 2=quite interested, 3=some interest, 4=very little interest, 5=not interested.

A.3.2 Mean Differences in Expected Income and Enjoyment of Humanities Graduates

The expected income and enjoyment patterns in Table 6 were re-estimated by taking individual differences of the other majors compared to humanities for each individual and estimating the mean differences to provide direct tests of the statistical significance of the differences in both expected income and enjoyment. For expected income the analysis of individual differences estimates the mean of the income differences; for expected enjoyment the analysis estimates the “mean” of the enjoyment differences where the following values are assigned to the ordinal enjoyment variable: “very enjoyable” (1), “somewhat enjoyable” (2), “somewhat unenjoyable” (3) and “very unenjoyable” (4). The results are reported in Table A3. All the differences are highly statistically significant.

	Expected Income Difference ($1000s)	Expected Enjoyment Difference
	Career Type: Non-college Jobs	
Science	7.769	1.727
	(2.000)	(0.383)
Business	11.154	1.500
	(2.281)	(0.435)
Professional	6.846	1.583
	(1.850)	(0.417)
	Career Type: College Jobs	
Science	12.182	2.143
	(2.850)	(0.221)
Business	8.773	1.857
	(2.475)	(0.221)
Professional	13.045	1.286
	(3.348)	(0.277)

Notes: Standard errors in parentheses

Table A3: Mean Differences in Expected Income and Enjoyment of Humanities Graduates

A.4 The Berea Task Data

In most panel data sets it is typically necessary to impute tasks associated with a particular job on the basis of the job's occupation.[22] In addition, many primary sources of occupational level task information provide only qualitative information regarding how important the task is in the job, without distinguishing between the skill level at which the task is performed. Other sources, such as the DOT, may provide some information on the level at which tasks are performed, but not on whether the task is always performed at the same level or the relative importance of the tasks in terms of their share in total time spent on the job.[23] The task measures in the BPS were collected to address these traditional limitations.

A particularly innovative feature of the Berea task data is that, unlike task data sources such as the DOT, the level at which the task is performed is not constrained to a single value from a set of

[22]Recent evidence suggests that this type of imputation matters in practice. Bowlus, Mori and Robinson (2016) and Handel and Autor (2013) show that tasks vary significantly within three-digit occupations.

[23]While the conceptual usefulness of knowing how individuals divide their work time among various job tasks has been recognized (Gathmann and Schoenberg, 2010), direct information of this type has not been available from existing data sources.

mutually exclusive levels. In the Berea data individuals are asked for both the importance rating and the time allocation for all four levels levels at which each task can be performed. Thus, on the job an individual may spend some time following instructions as well as some time supervising.[24] Previous task based research has not been very successful in isolating the kind of people skills associated with systematically higher earnings or high level careers. Analysis with the BPS task measures, however, suggest that the combination of level and time allocation information may be a fruitful approach.

The measures are in the spirit of information available in the DOT, describing how tasks relate to People, Information, and Objects. Task information is collected directly from the worker. Then, the fact that this information is collected yearly allows us to construct the first longitudinal job-level task information, starting at the very beginning of careers. A unique feature of our task measures comes from collecting time allocation information related to the task measures. Specifically, the survey documents the percentage of time in a year that is spent interacting in three general task categories: People, Information, and Objects. Further, within each of these general task categories, respondents report the percentage of time spent performing four different sub-tasks, which are ordered by skill.[25] Thus, it is possible to compute the proportion of the worker's time on the job that is spent on twelve different sub-tasks.

The BPS asks respondents about how their job requires them to relate to "people", "information" and "objects" on scales similar to the analyst ratings in the well known Dictionary of Occupations (DOT) used in much of the current literature on job tasks. For the "people" category the respondents are asked about 4 ways in which they can interact: "following instructions", "persuading others", "supervising others" and "exchanging ideas". As in the DOT, interaction in the categories "supervising others" and "exchanging ideas" represent higher levels in the "people" category than "following instructions". For each of the categories there are four levels of interaction. An innovative feature of the BPS data is that in addition to information on how important each of these forms and levels of interaction are, commonly available in other data sets, respondents are also asked to specify the fraction of their time on the job in in each of the three categories, "people", "information" and "objects", and at each of the four possible levels in each category. This provides a direct measure of time spent on a variety of tasks at a variety of levels, that is readily interpretable as the task

[24] In the DOT the levels within "people", "data" and "things" are mutually exclusive and the analyst chooses one to represent the job.

[25] For example, the sub-tasks in the Information category are: entering data, gathering data, analyzing data, and using data analysis to develop solutions.

bundle supplied by the worker on the job. Our analysis suggests that this measure is a significant improvement over measures that are missing the combination of how much time is spent at each level of each task and rely instead on measures of importance.

In creating an appropriate task measure for the BPS data several issues were considered. Unlike previous studies involving task measures, all the respondents are college graduates, and all from the same college. The common measures of manual and cognitive tasks, especially without a time allocation, are not very suitable in our context. We are looking at more of a continuum of jobs into which relatively similar people are being allocated. Some may have jobs with a bit more responsibility or more of a managerial role that use, for example, good people interaction skills. In the previous literature these more subtle differences have been difficult to pick up. Common factor analysis related approaches often have difficulty identifying anything much beyond "cognitive", "fine motor skill" and "physical strength" skills.

The time allocation questions in the BPS are asked following the more standard "importance" questions after a pre-amble as follows:

> "NOW think about the **TOTAL time** that you spend **interacting with PEOPLE as part of your JOB1.** .. indicate what percentage of this Total time is spent interacting in each of the four ways. **Note:** each percentage should be between 0 (the item plays no role) and 100 (all interactions come from the one item) **and the four percentages should sum to 100.**"

This gives the percentage of time at each level *within* each of the three categories. A subsequent series of questions measures the percentage of total job responsibilities for the three categories:

> "Now think about your Total job responsibilities on your JOB1. ... indicate the percentage of your responsibilities that involve interacting with PEOPLE, INFORMATION and OBJECTS .... Each percentage should be between 0 and 100 and the three percentages should sum to 100."

There are three task types each performed at four possible levels, giving up to 12 components of a job that the worker may supply positive amounts of time to. Using the percentage measures above, the worker's job is characterized by the percentages for these 12 components.

A.4.1 Distribution of Tasks in the BPS Data

All the college graduates in the BPS data work at jobs that involve interaction with people, information and objects, though, in terms of time allocation, the interaction with people is the most important. The first row of Table A4 shows the breakdown. Over 50% of the time of Berea graduates involves interaction with people and only 15% involves interaction with objects. The remaining rows report the percentages for the "importance" ratings commonly used in task measures. For Berea graduates, interaction with people is the most important aspect of the job. It is very important for 84% of the graduates, and moderately or very important for 96%. However, while the large fraction

	People	Information	Objects
Time Allocation (%)	51.62	33.49	14.94
(Standard Error)	(.361)	(.293)	(.266)
Not important (%)	0.56	1.37	30.12
Somewhat important (%)	3.31	7.04	29.06
Moderately important (%)	11.94	29.37	21.63
Very important (%)	84.18	62.22	19.20

A4: Time Allocation and Importance for Task Types

of time involved and high level of importance of the people related tasks is a common feature for the Berea graduates, there are very clear differences in the amount of time devoted to the various levels within the task types, in terms of the jobs undertaken by the individuals in the three different career paths, *CC, NC* and *NN*.

A.5 Relative Wage Growth in the CC Group by GPA

The low GPA graduates in the *CC* group show very slow wage growth after the first two years as shown in the following Figure A1.

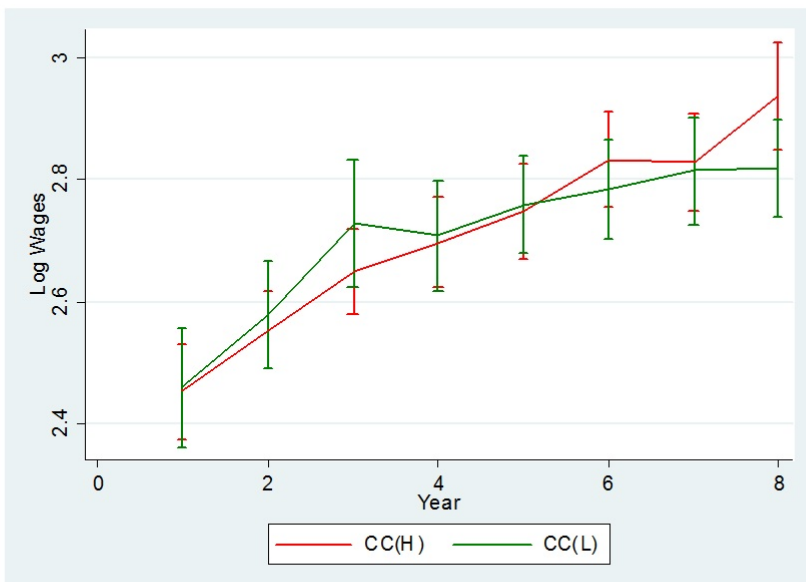

Figure A1: Log Real Hourly Wages by GPA for CC Career