The Use of Major-Related Skills by Early Career College Graduates

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August 15, 2022

Abstract

In this paper, I develop a measure of the match between a college major and an occupation. This measure estimates the Euclidean distance between the skills that are required of an occupation and the skills that are required of the occupation(s) that a college major trains individuals for. Using this skill distance measure, I find considerable heterogeneity across college majors in the extent to which graduates work in occupations that require major-related skills. Health/medicine, education, and business graduates use major-related skills in their jobs to a greater extent than graduates of other majors. Furthermore, in contrast with the majority of the literature, graduates of several arts and humanities majors use major-related skills in their jobs to a greater extent than graduates of mathematics, physical sciences, or biology programs. This is a result of the broad applicability of arts and humanities related skills across the occupation distribution, and casts doubt on the idea that STEM majors are better matched in the labor market than arts and humanities majors. This paper is also the first to establish that college graduates of nearly every major are employed in better matching occupations than would be predicted by chance if college graduates were randomly assigned occupations.

JEL Classification: I20, I23

Keywords: Education mismatch, horizontal mismatch, overeducation, skills, college skills

*I would like to offer my sincere thanks to Hiromasa Tsuchiya for his excellent work as a Research Assistant on this project. I would also like to thank participants at the 2022 Annual Meetings of the Canadian Economics Association for their helpful feedback on this project. I would also like to acknowledge having received funding for this project from the SMUworks program at Saint Mary's University. All errors or omissions are mine alone. Declarations of interest: none.

1 Introduction

Are college graduates able to find employment in jobs that require the skills that are associated with their major? This is a question that is of broad interest to students, educators, and policy makers alike. Students have been shown to prefer majors that have a high probability of leading to employment in related occupations (Freeman & Hirsch 2008, Long *et al.* 2015, Arcidiacono *et al.* 2020, Han & Winters 2020). Educators alter their curriculums so that course content aligns with the skills and knowledge expectations of employers. Policy makers invest in colleges with the objective of providing students with skills that will be valued in the labor market. Increasingly, these public investments are targeted towards increasing enrollment in majors that are expected to produce graduates with strong labor market outcomes. Ohio and Florida are among the states that provide additional funding to colleges that produce graduates in majors of interest[1].

However, despite broad interest in the question of whether college graduates use the skills that are associated with their education, our understanding of this question is incomplete. For some majors, it is relatively straightforward to determine that graduates tend to apply major-related skills in their jobs. 78% of nursing graduates under the age of 30 are employed as Registered Nurses[2], an occupation that clearly requires skills that are associated with a nursing degree. However, for some majors, it is difficult to determine whether graduates are employed in occupations that make use of major-related skills. Consider history degrees. These degrees train students in skills that are not unique to occupations that would traditionally be considered a match for a history degree. Editors, for example, require the written communication skills that are closely associated with a history degree, even though they are generally not required to possess the range of historical knowledge that a history graduate would have. In terms of the extent to which they use the skills that are associated with a history degree, Editors clearly lie in between Museum Curators, who require nearly all of the skills that are associated with a history degree, and Sheet Metal Workers, who require almost none of the skills that are associated with a history degree. This type of heterogeneity, combined with history graduates being highly dispersed across occupations[3], makes it difficult to assess whether history graduates tend to work in occupations that require major-related skills.

The majority of the literature on major/occupation matching has utilized binary measures to indicate whether an individual is employed in a matched or mismatched occupation. By definition, a binary measure is unable to capture heterogeneity in the *extent* to which graduates use major-related skills in their jobs. In this paper, I develop a measure of the distance between the skill requirements of an individual's occupation, and the skills that are required of the occupation (or narrow set of occupations) that their major trains individuals for. Skill measures for each occupation are obtained from the O*NET database[4]. This distance score will be

[1]See this link for a list of majors that are eligible for addition funding in Florida.

[2]Author's calculation from the 2015-2019 waves of the American Community Survey

[3]The most common occupation for History graduates under the age of 30 is "Elementary and Middle School Teachers", which employs only 6% of History graduates.

[4]The O*NET database contains, for each occupation, a measure of the *importance* of 35 different skills for that occupation, as well as a measure of the *level* of these skills that are required. The importance scale captures the frequency with which a skill is

small if an individual is employed in an occupation that has similar skill requirements as the occupation that their major trains individuals for, even if their occupation is not traditionally considered to be a match for their major. However, if they are employed in an occupation that requires very few major-related skills, the distance score will be large. As an example, an individual with an education degree who is employed as a "Training and Development Specialist" will have a smaller distance score than someone with the same degree who is employed as a "Construction Equipment Operator", since the former occupation requires similar skills to those of a Teacher, the most closely matching occupation to an education degree.

Using American Community Survey (ACS) data, I examine distance scores of individuals under the age of 30 who possess a bachelor's degree as their highest level of education. The focus is placed on younger workers who have less labour market experience since the skills that these workers possess are expected to be more closely aligned with the skills that are asssociated with their majors. Individuals with graduate degrees are eliminated since the field of their graduate degree is unknown, and graduate degree fields frequently do not correspond with undergraduate majors (Altonji & Zhong 2021).

After controlling for demographic characteristics, the average distance score is calculated for graduates of 24 different majors. The findings suggest that there is considerable heterogeneity in average distance scores across different majors. Consistent with the existing literature on major/occupation matching, graduates of the vocationally-oriented majors of health/medicine, education, and business have the greatest tendency to be employed in occupations that require major-related skills. The STEM majors of computer science and engineering are also among the majors that produce the best matching graduates. However, the remaining STEM majors of mathematics, biology, and physical sciences (which includes chemistry and physics) are among the majors that produce graduates with the highest average distance scores, indicating that graduates of these majors are among the least likely to use use major-related skills in their jobs.

Arts and humanities majors also vary in their average distance scores. Cultural/ethnic studies and languages graduates are among the most poorly matched of all college graduates. However, graduates of some other arts and humanities majors fare considerably better. Social science, history, and library science graduates are employed in occupations that are, on average, closer to the occupations that they were trained for than graduates of mathematics, biology, or physical sciences. This stands in contrast with the academic literature which tends to find that STEM graduates (with the occasional exception of biology graduates) are nearly always better matched than arts and humanities graduates (Robst 2007, Lemieux 2014). Furthermore, it seems to be contradicted by a result in this paper showing that graduates of all STEM majors are more likely to be employed in occupations that are perfect matches for their majors than graduates of the listed arts and humanities majors. The reason for this discrepancy lies in the fact that arts and humanities graduates who are not employed in

required on the job, whereas the level scale captures whether a worker requires a basic level of the skill or an advanced level of the skill. For example, the importance of mathematics skills is higher than the level of mathematics skills for Cashiers, since Cashiers are frequently required to use mathematics but do not perform advanced calculations.

traditionally matching occupations still tend to be employed in occupations that require major-related skills. STEM graduates who are not employed in traditionally matching occupations, on the other hand, rarely use major-related skills in their jobs.

To place distance scores in context, I compare distance scores to a hypothetical benchmark distance score that would arise if college graduates of major X were to be randomly assigned occupations from the occupation distribution of graduates of majors *other than* major X. This will indicate whether graduates of major X use skills that are related to major X more than the skills that are related to other majors. In other words, are college graduates better than randomly sorted into occupations that require major-related skills? The results from this exercise show that graduates of 23 out of 24 majors are employed in occupations that require major-related skills to a greater extent than the skills that are associated with other majors. The lone exception to this is history.

Even beyond history, graduates of arts and humanities majors tend to only marginally beat chance at being assigned to occupations that require skills that are specific to their majors. Although on the surface this seems to indicate that graduates of these majors are poorly matched, this is not the case, as is reflected by their average distance scores. The reason for this discrepancy is that the hypothetical random assignment distance scores are lower for graduates of arts and humanities programs, since the skills that are associated with these degrees are more widely used across the distribution of occupations that employ college graduates than are the skills that are associated with STEM majors. To put this another way, the skills that are associated with arts and humanities degrees are less unique, and are applicable in occupations that employ graduates of other majors to a greater extent than the skills that are associated with STEM degrees.

The remainder of this paper is structured as follows. Section 2 reviews related literature. Section 3 reviews the data sources and provides an overview of the methodology. Section 4 reviews the results. Section 5 concludes.

2 Literature Review

Since the 1970s, a large literature has emerged which examines the extent to which university graduates are employed in occupations that are require the skills that are associated with their education. This literature emerged after the publication of "The Overeducated American" (Freeman 1976), which claimed that the supply of young Americans with tertiary education was outstripping demand for highly educated labour, thus pushing some university graduates into low paying occupations that do not require a university degree. Motivated by this work, the earliest related literature compared two unidimensional skill measures: an individual's level of education, and the level of education that is required for their occupation. This literature has been well summarized in numerous literature reviews including McGuinness (2006), Leuven & Oosterbeek (2011), Quintini

(2011), and McGuinness *et al.* (2018), however some of the key conclusions are summarized here.

This literature has predominantly used the terms "overeducated" and "undereducated" to reflect situations in which an individual possesses more or less education than is required for workers in their job. Estimated rates of overeducation vary considerably. The majority of the literature has estimated that somewhere between 20% and 40% of the workforce possesses more education than is required for workers in their job (Sicherman 1991, Groot & Van Den Brink 2000, Hartog 2000, McGuinness & Bennett 2007, Chevalier & Lindley 2009, Verhaest & Omey 2010, Carroll & Tani 2013, Meroni & Vera-Toscano 2017, Orbay *et al.* 2021), although rates of overeducation as high as 60% have been documented among early career university graduates in Europe (Baert *et al.* 2013). Rates of undereducation have been documented less frequently, although it has generally been found that undereducation is less common than overeducation, with typical estimates falling between 10-25% (Sicherman 1991, Groot & Van Den Brink 2000, Leuven & Oosterbeek 2011).

Concerns about the incidence of overeducation are primarily attributable to lower earnings for overeducated workers relative to well-matched individuals with the same quantity of education (Duncan & Hoffman 1981,McGuinness *et al.* 2018, Cultrera *et al.* 2022). Furthermore, while some individuals who are overeducated subsequently move into occupations that are appropriate matches for their education, overeducation has been shown by some researchers to be a trap, with individuals who accept jobs for which they are overeducated being less likely to find employment that matches their education in the future (Baert *et al.* 2013, Clark *et al.* 2017, Meroni & Vera-Toscano 2017). Rates of overeducation have also been shown to vary across graduates of different majors, with papers that have examined this consistently finding that graduates of vocationally-oriented majors, such as health or education, have the lowest rates of overeducation (Ortiz & Kucel 2008,Carroll & Tani 2013).

Employment in an occupation for which one is overeducated is likely to reflect a situation in which a worker's skills will not be fully utilized. However, this picture is incomplete. An individual may be employed in an occupation that requires the *level* of education that they have, but which requires a different *type* of education. In a statement that encapsulates the heterogeneity in skill types across degrees of the same level, Capsada-Munsech (2019) states that "Individuals with college degrees from different felds of study are considered to have the same skills level, even if one studied medicine and the other one law".

In response to criticisms such as the above, researchers have developed the term *horizontal mismatch* to reflect a situation in which an individual is employed in an occupation that is a good match given the quantity of education that they possess, but is mismatched considering the type of education that they possess. Sloane (2003) uses the example of an English major who is employed as a Statistician. The earliest work in this literature, by Robst (2007), uses self-reported measures of mismatch and determines that approximately 20% of new college graduates report working in occupations that are unrelated to their major. Nordin *et al.*

(2010) finds a similar rate of mismatch using an objective measure of mismatch that examines whether an individual is employed in the occupation that is most closely associated with their major. Similar overall rates of major/occupation mismatch have since been documented by Lemieux (2014) using a self-reported measure of mismatch.

There is considerable variation across majors in the extent to which graduates are employed in occupations that are unrelated to their major. Arts and humanities graduates are consistently found to be more likely to be employed in horizontally mismatched occupations (Robst 2007, Nordin *et al.* 2010, Lemieux 2014, Abel & Deitz 2015,Verhaest *et al.* 2017). Graduates of vocationally-oriented majors such as health and education are consistently found to have low rates of major/occupation mismatch (Nordin *et al.* 2010, Lemieux 2014), as are graduates of STEM majors such as computer science and mathematics (Lemieux 2014, Kinsler & Pavan 2015).

However, despite this expansion in the literature to examine whether individuals are employed in occupations that match their major, there is still little to be said about the *strength* of the match between an individual's major and their occupation. Graduates of majors in the arts and humanities have been found to be employed in a wider variety of occupations than graduates of vocationally-oriented majors (Ransom & Phipps 2017), making an assessment of the strength of a match important for fully characterizing differences in matching across majors. One notable study that has examined the strength of a match is Reis (2018), the work that is most closely associated with this paper. Reis (2018) develops a continuous measure of the match between an individual's major and occupation based on whether job analysts list similar task requirements for an individual's actual occupation and the occupation that is most closely associated with their major. Using this continuous measure of mismatch, the author concludes that there is considerable heterogeneity in the extent to which mismatched graduates are employed in occupations that have similar task requirements as the occupation that is associated with their major. Similarly, Kracke & Rodrigues (2020) has documented that vocational graduates in Germany have a tendency to be employed in occupations that require similar levels of cognitive skills as the occupations that they were trained for.

This paper expands upon the literature in the following ways. First, I provide the first estimates of the skill distance between majors and occupations using a broad range of continuously measured skill requirements from O*NET. Second, using these skill distances, I am able to provide the first estimates of the extent to which graduates of different majors are employed in occupations that require major-related skills. Third, I provide, to the best of my knowledge, the first estimates that compare major/occupation mismatch to a situation in which college graduates are randomly assigned occupations.

3 Data and Methodology

This project uses the American Community Survey (ACS) five year data file that covers the years 2015-2019. Individuals who are aged 30 or over at the time of the survey are eliminated from the sample. These individuals are eliminated so that the data comprises recent college graduates whose skills are expected to closely correspond with the skills that are associated with their education. Furthermore, individuals with no observable major or occupation are also eliminated from the sample, as are individuals who are self-employed. I also eliminate individuals who report that they possess bachelor's degrees in skilled trades that are more common among individuals with an associate's degree. Finally, individuals who report having completed more than one major are eliminated due to the difficulties of assessing distance between an occupation and multiple majors. This leaves a sample of 295,666 individuals, with demographic characteristics that are listed in Table 1. As can be seen, the sample is majority female and majority white. The young average age reflects the fact that the sample comprises only individuals under the age of 30. Table 2 shows the proportion of the sample that studied each of the 24 majors that are considered. It is clear that the most common major by far is business, which comprises 20% of the sample. Health/medicine, engineering, education, and social sciences also comprise at least 7% of the sample.

Table. 1. Sample Means of Demographic Characteristics

	(1)
	Mean
Female	0.56
White	0.70
African-American	0.06
Asian American	0.10
Hispanic	0.11
Age	25.62
N	295,666

This table contains the sample means of demographic characteristics of interest. Means for all variables, with the exception of age, are proportions.

The primary focus is on the similarity between the skill requirements that are associated with an individual's actual occupation and the skill requirements of the occupation(s) that their major trains individuals for. The skill measures that are used for this analysis are taken from the O*NET database. O*NET contains measures of the extent to which an occupation requires 35 different skills. These skills range from "Reading Comprehension" to "Equipment Selection", and from "Persuasion" to "Mathematics".

I link an individual's recorded 6-digit[5] Standard Occupation Classification (SOC) occupation to the skill requirements that are associated with that occupation as defined by O*NET. I then aggregate these skills using Principal Component Analysis. For individual i employed in occupation o, the jth principal component is defined as $Comp_{j,o,i}$. For ease of interpretation, these principal components are placed on a standard normal scale,

[5]The ACS does not record every occupation at the 6-digit level. In several instances, occupational data is only available at the 5-digit or 4-digit level. The skill requirements of these occupations are calculated as an equally weighted average of the skill requirements of each 6-digit occupation within the 5-digit or 4-digit occupation group.

Table. 2. Percentage of Graduates of Major

	(1)
	Percentage
Agriculture	1.32
Environment/Conservation	1.11
Architecture/Land	0.67
Cultural/Ethnic Studies	0.41
Communications/Journalism	6.02
Computer Science	4.08
Education	7.79
Engineering	8.52
Languages	0.78
Family and Consumer Studies	1.04
Law	0.18
Library Science	2.68
Biology	6.49
Mathematics	1.18
Recreation/Fitness	2.59
Philosophy/Religion	1.08
Physical Sciences	2.55
Psychology	6.14
Public Administration	1.23
Social Sciences	7.19
Visual/Performing Arts/Music	5.96
Health/Medicine	9.24
Business	20.06
History	1.70
N	295,666

This table contains the percentage of the sample who studied each listed major.

with a value of 0 indicating the mean level of the component in the population. The corresponding eigenvalue for component j, which measures the proportion of variation in the skill space that is captured by component j, is denoted as $Eigen_j$.

The ACS data also records an individual's major for their bachelor's degree. Each major is matched to it's corresponding 2-digit Classification of Instructional Programs (CIP) code. I use 2-digit CIP major groups in order to ensure that the sample size for each major is large enough so as to be able to draw conclusions regarding major/occupation matches. Each major is linked to occupations using a CIP-SOC crosswalk from the National Center for Education Statistics, an approach that has been used by Abel & Deitz (2015) and Manuel & Plesca (2020). This crosswalk links majors to the occupation, or narrow set of occupations, for which that major trains individuals. For example, a Bachelor's of Education program trains individuals to be a teacher. However, this crosswalk links highly refined 6-digit CIP codes to occupations, as opposed to aggregated 2-digit CIP codes. Therefore, each 6-digit CIP major is linked to it's corresponding 2-digit CIP major, and an occupation is considered to be a match for one's major so long as any of the 6-digit CIP groups within one's 2-digit CIP group links to that occupation[6].

Linking each of the occupations that major m trains individuals for to their corresponding skills results in a set of skills for each individual 2-digit CIP group. For individual i who studied major m, the resulting vector of skills that matches to their major is denoted as $\mathbf{Comp_{j,m,i}}$. The elements of this vector are denoted as $Comp_{j,o_m,i}$, where o_m is an occupation that matches to major m. The Euclidean distance between the skills that are associated with individual i's actual occupation, and the skills that are associated with the occupations that match with their major, is calculated as follows:

$$\mathbf{Distance_{o,m,i}} = \sum_{j=1}^{N_j} \sqrt{Eigen_j * (\mathbf{Comp_{j,m,i}} - Comp_{j,o,i})^2} \tag{1}$$

This produces a vector of distances between individual i's major and individual i's occupation. Each component of this vector is denoted by $Distance_{o,o_m,i}$. If one of the elements of $\mathbf{Distance_{o,m,i}}$ is equal to 0, this indicates that individual i is employed in an occupation that is considered to be a perfect match for graduates of their major. However, if none of the elements of this vector are equal to 0, then the *average* of the elements of $\mathbf{Distance_{o,m,i}}$ are taken to be the distance between individual i's occupation o and their major m[7]. This can be expressed as:

[6] As an example of this, "Animal Sciences" is a 6-digit CIP major that trains individuals for the occupation of "Animal Scientist". Since Animal Sciences is contained within the 2-digit CIP group "Agriculture", Animal Scientists are considered to be matched if they studied Agriculture.

[7] When taking the average distance between one's actual occupation and the average occupation that matches to one's major, I exclude a few occupations that match to one's major. These excluded occupations are primarily managerial or supervisory in nature, or are one's that involve post-secondary teaching. This is done because these occupations require skills that are similar to those of occupations that are unlikely to be considered as a good match for one's major. For example, consider an individual who graduates from a biology program. While a "Natural Sciences Manager" is without a doubt a good match for their field, other managerial occupations are unlikely to be considered as such despite having similar skill requirements as "Natural Sciences Managers".

$$Distance_{o,m,i} = \begin{cases} 0 \quad if \quad \exists \quad Distance_{o,o_m,i} = 0 \quad \mathcal{E} \quad \mathbf{Distance_{o,m,i}} \\ \sum\limits_{o_m} \frac{Distance_{o,o_m,i}}{N_{o,m}} \quad otherwise \end{cases} \tag{2}$$

Where $N_{o,m}$ denotes the number of occupations o_m that match to major m. A distance score of 1 indicates that on average, the skills that are required for one's actual occupation are 1 standard deviation away from the skills that are required of the nearest occupation that is a direct match for their major.

Table. 3. Distance Scores for Select Major/Occupation Pairs

Mathematics	Distance
1. Market Research Analysts And Marketing Specialists	0.57
2. Accountants And Auditors	0.60
3. Other Social Scientists	0.63
4. Compensation, Benefits, And Job Analysis Specialists	0.63
5. Operations Research Analysts	0.64
Education	Distance
1. Other Community And Social Service Specialists	0.45
2. Social And Human Service Assistants	0.45
3. Probation Officers And Correctional Treatment Specialists	0.45
4. Tutors	0.52
5. Business Operations Specialists, All Other	0.52
Law	Distance
1. Court, Municipal, And License Clerks	0.5
2. Other Information And Records Clerks	0.51
3. Human Resources Assistants, Except Payroll And Timekeeping	0.54
4. Interviewers, Except Eligibility And Loan	0.57
5. Insurance Claims And Policy Processing Clerks	0.57
Engineering	Distance
1. Biomedical And Agricultural Engineers	0.58
2. Petroleum, Mining And Geological Engineers, Including Mining Safety Engineers	0.6
3. Physical Scientists, All Other	0.71
4. Computer Systems Analysts	0.73
5. Information Security Analysts	0.73

This table contains, for the 4 majors that are listed, the occupations with the 5 smallest distance scores that are not considered to be perfectly matched for graduates of that particular major.

For illustration purposes, Table 3 lists the 5 occupations with the smallest non-zero distance scores, for graduates of select majors. These are occupations that are not considered to be matches for the major according to data from the NCES, but that are estimated as having similar skill requirements to these occupations. Intuitively, it is clear that these listed occupations require skills that are associated with the listed majors.

3.1 Summary Statistics

Given that the distance scores are calculated as the Euclidean distance between vectors of normalized skills, the distance score can be interpreted as the number of standard deviations between the skills requirements that associated with one's occupation and the average skill requirements that are associated with their major. At the mean, this distance score is approximately 0.62. This distance score is, however, heavily influenced by a large mass of 0s, which reflect individuals who are employed in an occupation that is a perfect match for their major. 39.3% of the sample is employed in a perfectly matched occupation. Among those who are not perfectly matched, the average distance score is 1.02.

Figure 1 shows the kernel density estimates of distance scores for individuals who are not employed in an occupation that is a perfect match for their field of study. As can be seen, there is variation in the distance score, with the largest mass of individuals being located between 0.5 and 1.5 standard deviations away from the occupations that they were trained for.

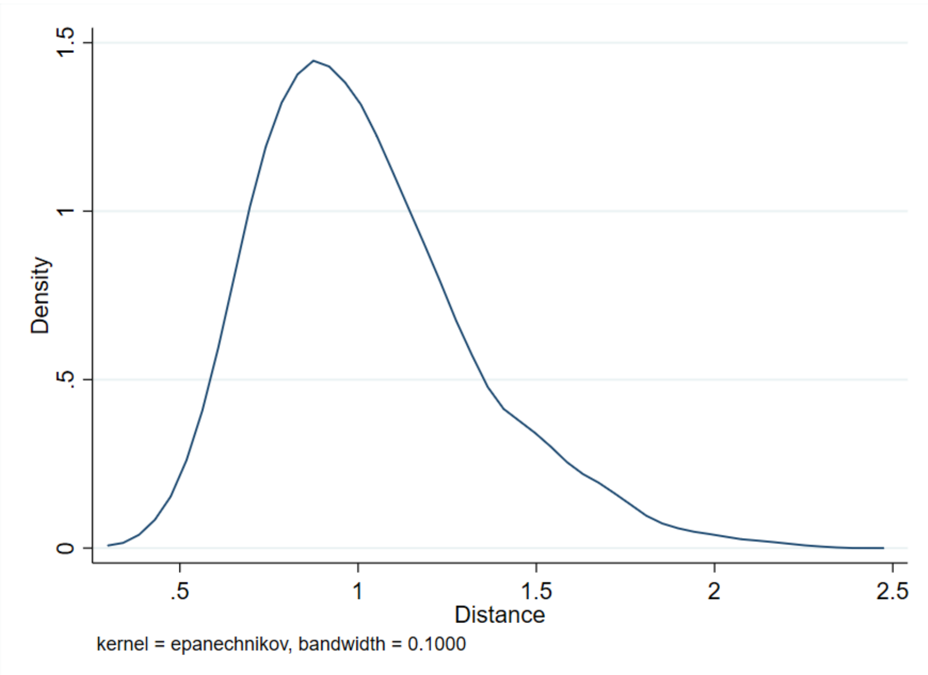

Fig. 1

4 Results

I examine the probability that an individual becomes employed in an occupation that is a perfect match for their major. A dummy variable $Perfect_i$ is created, taking on a value of 1 if an individual is employed in a perfectly matching occupation, and a value of 0 otherwise. This is analogous to the objective binary matching variables that are prevalent in the literature (Nordin *et al.* 2010, Abel & Deitz 2015).

I estimate the probit model in Equation 3.

$$Pr(Perfect_i = 1) = \Phi(\beta_0 + \boldsymbol{\beta_1 X_i} + \boldsymbol{\beta_2 Major_i} + \epsilon_i) \tag{3}$$

Where $\boldsymbol{X_i}$ is a vector of demographic characteristics that include; gender, age, race, estimated graduation year[8], and state of residence. $\boldsymbol{Major_i}$ consists of a set of dummy variables for each major. The predicted perfect match rates for each major, sorted from highest to lowest, are reported in Table 4.

The results reported in this table are consistent with the results that have been reported in the literature to date. Business, education, and health/medicine graduates all have high perfect match rates, with more than two-thirds of recent graduates of these majors working in perfectly matched occupations. Computer science and engineering graduates also have perfect match rates of 50% or above. At the opposite end of the spectrum, fewer than 5% of graduates of history, languages, library science, or cultural/ethnic studies work in perfectly matching occupations.

$$Distance_i = \beta_0 + \boldsymbol{\beta_1 X_i} + \boldsymbol{\beta_2 Major_i} + \epsilon_i \tag{4}$$

I proceed by estimating Equation 4, with the predicted average distance for each major reported in Table 5, with majors listed in ascending order. It is clear from this table that the ranking of majors by average distance is similar to the ranking of perfect match probabilities. Health/medicine, business, education, and computer science are the majors with the lowest average distance scores. This indicates that graduates of these majors, all of which have high perfect match rates, tend to be employed in occupations that require major-related skills. Cultural/ethnic studies and languages graduates have low perfect match rates as well as high average distance scores.

However, there are several majors for which the results reported in Tables 4 & 5 diverge. The STEM fields of physical sciences, mathematics, and biology all have high average distance scores. In fact, the distance scores for these 3 STEM majors exceed the distance scores for social science, history, and library science majors, despite

[8] An individual's estimated graduation year is calculated as the present year minus age plus 22.

the fact that the latter majors have lower perfect match rates. This difference in rankings can be interpreted as follows. While graduates of the aforementioned STEM majors have a higher likelihood of being employed in perfectly matching occupations, those who are not perfectly matched are less likely to make use of major-related skills in their jobs. Graduates of social science, history, and library science programs, on the other hand, are more likely to use major-related skills in their jobs when they are not perfectly matched.

This is clearly demonstrated in Table 6, which shows the average distance scores for graduates of each major who are *not* employed in a perfectly matching occupation. From this table, it is clear that graduates of STEM programs have a tendency to be poorly matched if they are not employed in an occupation that is a perfect match for their major. Graduates of arts and humanities programs and vocationally-oriented programs have a greater tendency to be employed in occupations that require major-related skills when they are not perfectly matched. The fact that highly occupation specific majors such as education and health/medicine produce graduates who use major-related skills even when they are not perfectly matched may seem surprising. Even though graduates of these majors are trained for highly specific occupations, those who do not find employment in these occupations are still observed to be employed in occupations that require some major-related skills.

4.1 Random Assignment

Although the previous subsection compares the average distance scores of graduates from different majors, it is not immediately apparent whether a given distance score reflects a good match or a poor match. In this subsection, I estimate hypothetical benchmark distance scores that would arise if graduates of major X were to be randomly assigned an occupation from the occupational distribution of graduates of *other majors*. This benchmark distance scores is denoted by $BenchmarkDistance_i$, and captures the distance between the skills that are associated with individual i's major and the skills of the occupation to which they were randomly assigned.

$$BenchmarkDistance_i = \beta_0 + \boldsymbol{\beta_1 X_i} + \boldsymbol{\beta_2 Major_i} + \epsilon_i \tag{5}$$

The model in Equation 5 is estimated, with the margins[9] for each major being reported in Table 7 in ascending order. It is clear from examining this table that if college graduates were randomly assigned to occupations that employ graduates of other majors, business graduates would be the best matched. In other words, the skills that are associated with a business degree are more broadly applicable across the occupation distribution of college graduates than the skills that are associated with any other major. Perhaps surprisingly, health/medicine skills rank as the second most broadly applicable.

After the aforementioned majors, it is clear that the majors that would produce the best matched graduates

[9]These margins are estimated on the basis of the actual observed characteristics of individuals.

under random assignment are predominantly arts and humanities oriented majors. The skills that are associated with these programs are applicable across a wide range of occupations that employ graduates of other majors. The largest benchmark distance scores are predominantly associated with STEM majors. The skills that are associated with these degrees are relatively unique within the occupation distribution, rendering them less applicable in occupations that employ graduates of other majors.

In order to examine how actual distance scores compare to the hypothetical benchmark distance scores, the difference between the two is estimated as $DistanceDifference_i = Distance_i - BenchmarkDistance_i$. The model in Equation 6 is estimated, with the estimated margins reported in Table 8.

$$DistanceDifference_i = \beta_0 + \boldsymbol{\beta_1 X_i} + \boldsymbol{\beta_2 Major_i} + \epsilon_i \tag{6}$$

The results indicate that graduates of every major except for history tend to use the skills that are related to their major to a greater extent than the skills that are associated with other majors. This indicates that college graduates tend to be better than randomly sorted into occupations that require major-related skills. However, there is considerable heterogeneity in the extent to which this is the case.

Unsurprisingly, the majors with the smallest average distance scores also tend to be the majors for which graduates are significantly better placed than random assignment. However, what is most notable about these results is that graduates of several arts and humanities majors are only marginally better placed than what would be predicted by chance. While on the surface, it may appear as though these graduates are poorly matched, these small gaps are primarily a result of the broad applicability of arts and humanities related skills to a wide range of occupations.

Graduates of STEM majors tend to be employed in occupations that require major-related skills to a greater extent than would be predicted by random assignment. While, as per the results in Table 5, graduates of some STEM majors tend to be poorly matched relative to graduates of most other majors, this is because the skills that are associated with these majors are relatively unique compared to the skills that are associated with other majors. This is as opposed to STEM graduates being relatively poorly *assigned* to occupations.

Table. 4. Perfect Match Probability

	(1)	
	Estimated Probability	Standard Error
Health/Medicine	0.70	(0.0036)
Business	0.68	(0.0024)
Education	0.67	(0.0041)
Computer Science	0.58	(0.0057)
Engineering	0.50	(0.0041)
Architecture/Land	0.45	(0.014)
Agriculture	0.39	(0.010)
Public Administration	0.37	(0.011)
Law	0.29	(0.023)
Family and Consumer Studies	0.28	(0.010)
Visual Arts/Performing Arts/Music	0.25	(0.0041)
Mathematics	0.18	(0.0084)
Environment/Conservation	0.17	(0.0081)
Communications/Journalism	0.17	(0.0035)
Psychology	0.16	(0.0036)
Physical Sciences	0.15	(0.0052)
Recreation/Fitness	0.14	(0.0052)
Philosophy/Religion	0.14	(0.0076)
Biology	0.12	(0.0029)
Social Sciences	0.075	(0.0024)
Languages	0.039	(0.0048)
History	0.039	(0.0037)
Library Science	0.013	(0.0015)
Cultural/Ethnic Studies	0.0034	(0.0019)
N	295,666	

Standard errors in parentheses

This table contains the estimated probability that a graduate of a given college major, listed in the rows, is employed in an occupation that is determined to be a perfect match for that major based on data from the National Center for Education Statistics. These perfect match probabilities are estimated as margins following estimation of Equation 3. The subsample that is used for this analysis consists exclusively of individuals who are under the age of 30, have completed a bachelor's degree as their highest level of education, and are employed. Graduates of select majors which are small is size and more typical of an associate's degree are eliminated.

Table. 5. Average Distance Scores

	(1)	
	Estimated Probability	Standard Error
Health/Medicine	0.31	(0.0037)
Education	0.32	(0.0042)
Business	0.33	(0.0027)
Computer Science	0.52	(0.0074)
Architecture/Land	0.55	(0.015)
Engineering	0.60	(0.0052)
Public Administration	0.64	(0.012)
Visual Arts/Performing Arts/Music	0.66	(0.0040)
Agriculture	0.67	(0.012)
Family and Consumer Studies	0.67	(0.010)
Law	0.69	(0.025)
Recreation/Fitness	0.73	(0.0051)
Communications/Journalism	0.77	(0.0037)
History	0.83	(0.0056)
Environment/Conservation	0.87	(0.0098)
Library Science	0.89	(0.0027)
Social Sciences	0.91	(0.0033)
Mathematics	0.92	(0.012)
Philosophy/Religion	0.95	(0.012)
Psychology	0.95	(0.0052)
Languages	0.98	(0.0082)
Physical Sciences	0.98	(0.0074)
Biology	0.99	(0.0043)
Cultural/Ethnic Studies	1.09	(0.014)
N	295,666	

Standard errors in parentheses

This table contains the average distance between the skills that are associated with an individual's occupation and the skills that are associated with the occupation(s) that are most closely associated with their college major, as determined by National Center for Education Statistics. The construction of the distance score is outlined in Section 3. The average distances are estimated as margins following estimation of Equation 4. The subsample that is used for this analysis consists exclusively of individuals who are under the age of 30, have completed a bachelor's degree as their highest level of education, and are employed.

Table. 6. Average Distance Scores (Conditional on Not Perfectly Matched)

	(1)	
	Estimated Probability	Standard Error
Recreation/Fitness	0.86	(0.0030)
History	0.86	(0.0047)
Visual Arts/Performing Arts/Music	0.89	(0.0021)
Library Science	0.90	(0.0023)
Communications/Journalism	0.92	(0.0022)
Family and Consumer Studies	0.94	(0.0055)
Law	0.98	(0.018)
Architecture/Land	0.99	(0.011)
Education	0.99	(0.0048)
Social Sciences	0.99	(0.0024)
Health/Medicine	1.01	(0.0028)
Languages	1.02	(0.0066)
Public Administration	1.03	(0.0083)
Environment/Conservation	1.05	(0.0058)
Business	1.05	(0.0022)
Agriculture	1.10	(0.0046)
Cultural/Ethnic Studies	1.10	(0.014)
Philosophy/Religion	1.11	(0.0095)
Biology	1.12	(0.0032)
Mathematics	1.12	(0.0084)
Psychology	1.14	(0.0040)
Physical Sciences	1.15	(0.0051)
Engineering	1.19	(0.0037)
Computer Science	1.25	(0.0039)
N	176,385	

Standard errors in parentheses

This table contains the average distance between the skills that are associated with an individual's occupation and the skills that are associated with the occupation(s) that are most closely associated with their college major, as determined by National Center for Education Statistics. The construction of the distance score is outlined in Section 3. Individuals who are employed in an occupation that is most closely associated with their major are eliminated from the sample. The average distances are estimated as margins following estimation of Equation 4. The subsample that is used for this analysis consists exclusively of individuals who are under the age of 30, have completed a bachelor's degree as their highest level of education, and are employed.

Table. 7. Distance Scores From Random Assignment

	(1)	
	Estimated Probability	Standard Error
Business	0.66	(0.0027)
Health/Medicine	0.76	(0.0034)
Family and Consumer Studies	0.78	(0.0091)
History	0.83	(0.0044)
Education	0.84	(0.0032)
Visual Arts/Performing Arts/Music	0.84	(0.0029)
Recreation/Fitness	0.88	(0.0035)
Communications/Journalism	0.90	(0.0028)
Library Science	0.90	(0.0025)
Public Administration	0.90	(0.0076)
Social Sciences	0.92	(0.0031)
Architecture/Land	0.93	(0.0071)
Agriculture	0.95	(0.0078)
Environment/Conservation	0.98	(0.0054)
Psychology	0.99	(0.0043)
Philosophy/Religion	1.02	(0.0083)
Law	1.04	(0.020)
Biology	1.07	(0.0033)
Languages	1.08	(0.0078)
Mathematics	1.08	(0.0094)
Computer Science	1.10	(0.0047)
Physical Sciences	1.13	(0.0051)
Engineering	1.14	(0.0035)
Cultural/Ethnic Studies	1.15	(0.013)
N	293,843	

Standard errors in parentheses

This table contains the average distance between the skills that are associated with the occupation(s) that are most closely associated with an individual's college major and the skills that are associated with *randomly assigned* occupations from the occupation distribution of graduates of different majors. The construction of the distance between a major and an occupation is outlined in Section 3. These distances are estimated following estimation of Equation 5.The subsample that is used for this analysis consists exclusively of individuals who are under the age of 30, have completed a bachelor's degree as their highest level of education, and are employed.

Table. 8. Distance Scores Relative to Random Assignment (Occupation Distribution of Bachelors Graduates)

	(1)	
	Estimated Probability	Standard Error
Computer Science	-0.58***	(0.0087)
Engineering	-0.54***	(0.0063)
Education	-0.51***	(0.0053)
Health/Medicine	-0.45***	(0.0050)
Architecture/Land	-0.38***	(0.017)
Law	-0.35***	(0.031)
Business	-0.33***	(0.0038)
Agriculture	-0.28***	(0.014)
Public Administration	-0.26***	(0.014)
Mathematics	-0.16***	(0.016)
Visual Arts/Performing Arts/Music	-0.17***	(0.0049)
Recreation/Fitness	-0.15***	(0.0063)
Physical Sciences	-0.15***	(0.0088)
Communications/Journalism	-0.13***	(0.0046)
Family and Consumer Studies	-0.11***	(0.014)
Environment/Conservation	-0.11***	(0.011)
Languages	-0.11***	(0.011)
Biology	-0.086***	(0.0055)
Philosophy/Religion	-0.069***	(0.014)
Cultural/Ethnic Studies	-0.059***	(0.018)
Psychology	-0.044***	(0.0066)
Library Science	-0.017***	(0.0036)
Social Sciences	-0.0099**	(0.0046)
History	-0.0010	(0.0072)
N	293,843	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table contains the difference between the calculated distance between an individual's actual occupation and the occupation(s) that are most closely matched with their major, and the distance between these major-related occupations and a *randomly assigned* occupation from the occupation distribution of graduates of different majors. The construction of the distance between a major and an occupation is outlined in Section 3. This gap between distances is estimated following estimation of Equation 6.The subsample that is used for this analysis consists exclusively of individuals who are under the age of 30, have completed a bachelor's degree as their highest level of education, and are employed.

5 Conclusion

When examining whether college graduates tend to become employed in occupations that require the skills that are associated with their degree, it becomes clear that graduates of some majors tend to be better matched than graduates of other majors. Consistent with earlier literature on the topic, graduates of vocational majors such as education, health/medicine, and business tend to be employed in well-matched occuaptions. Moreover, graduates of these majors tend to use major-related skills in their jobs even when they are not employed in perfectly matching occupations.

STEM majors, however, are more heterogenous in the extent to which they use major-related skills in their jobs. Engineering and computer science graduates tend to be very well-matched, and use major-related skills almost as frequently as graduates of the vocationally-oriented programs that are listed above. However, graduates of mathematics, biology, and physical sciences are less likely to use major-related skills in their jobs than graduates of nearly all other majors, including several majors in the arts and humanities.

This may seem surprising, and goes against the popular narrative surrounding the employment prospects of STEM graduates relative to arts and humanities graduates. Furthermore, it also stands in contrast with much of the literature on major/occupation matching, which has tended to find that graduates of most STEM majors are relatively well-matched. However, using the distance score that is developed in this paper, I find that the skills that are associated with STEM degrees are highly unique within the occupation distribution, and that STEM graduates who do not find employment in perfectly matching occupations tend to be poorly matched.Arts and humanities graduates, on the other hand, are relatively unlikely to be employed in perfectly matching occupations. They are, however, often employed in occupations that require major-related skills. This is due to the broad applicability of arts and humanities related skills across the occupation distribution.

The results in this paper cast doubt on the widespread assumption that graduates of arts and humanities programs are rarely employed in occupations that are good matches for their degree. Furthermore, given that large numbers of STEM graduates are employed in occupations that are unrelated to their major, these results raise questions surrounding the value of public policies that are aimed at increasing the number of STEM graduates coming out of colleges.

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