Letter

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Major-Occupation Match Quality: An Empirical Measure Based on Relative Productivity

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Abstract: The match quality between a worker's field of study in college and her occupation is an important labor market outcome. Yet this match quality is difficult to define and measure. We propose a new measure of major-occupation match quality based on relative productivity. A worker is well-matched if graduates from her major, working in her occupation, have high earnings relative to other major-occupation pairs. We show that some majors can be very well-matched or very badly matched (e.g. nursing), while others are never very well- or badly matched (e.g. humanities). Our measure has two desirable features: it is continuous, and it can be estimated in any data set including field of study, wage, and occupation.

Keywords: college major, match quality, mismatch, occupations, higher education

JEL Classification: J24, I26, J31, I24, I23

1 Introduction

Part of the return to a college major is the goodness-of-fit between the graduate's field of study and her eventual occupation. A graduate may enter a job which does not effectively use her skills, lowering the return on their educational investment (Kinsler and Pavan 2015). Research on these topics relies on measuring this goodness-of-fit between major and occupation.

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The study of horizontal mismatch, for example, relies explicitly on a definition of mismatch between education and occupation (Bender and Heywood 2011; Lemieux 2014; Nordin, ersson, and Rooth 2010; Robst 2007). In their review of measures of mismatch, Sellami, Verhaest, and Van Trier (2018) define three classes of measures from this literature: worker self-assessment (directly asking respondents about the match between their education and their occupation), job analysis (occupation classification by job analysts or similar expert opinion, e.g. O*Net), and realized matches (e.g. the education of the worker relative to the modal education of those in their job).

In this note, we propose a new measure of major-occupation mismatch based on relative productivity, as measured by the wage premium earned by graduates of different majors working in different occupations. We normalize these major premia to produce a measure of match quality ranging from −1 to 1, where −1 represents the lowest major-occupation premium and 1 represents the highest. The logic of our measure is straightforward: a major-occupation pair represents a good match if workers with that major-occupation combination have high productivity, as captured by earnings. Low-productivity major-occupation pairs – those with low earnings – represent poor matches.

Our measure differs from existing approaches in two ways. First, in contrast to the measures reviewed in Sellami, Verhaest, and Van Trier (2018), we derive our measure of match quality from wage data, giving it a direct link to worker productivity. Because of this, it can be estimated in any data set containing field of study, occupation, and pay. Second, the measure is continuous. While binary measures (“good match” or “bad match”) have some intuitive appeal, they are inherently arbitrary and miss much variation in match quality. Our measure allows the researcher to define “good” and “bad” match cut-offs if they wish, but it also says something important about majors that are never very well or very badly matched.

In the following sections, we will define our measure, outline the steps required to estimate it, and provide an illustration using data from the American Community Survey. Our illustration is fairly simple but can be adapted by other researchers as needed.

2 Measuring Match Quality

In previous work, we defined the specificity of college majors as the dispersion of average earnings of graduates from a given major across different occupations (Leighton and Speer 2020). By such a definition, specificity can be thought of as the potential for mismatch: a highly specialized major is one that has a much higher earnings premium in one occupation than it does in another. A general major, in contrast, earns a similar premium across all occupations and therefore has minimal scope for mismatch.

We extend that intuition here to measure the quality of matches between majors and occupations. We define match quality on a scale from −1 (worst overall match between any major and any occupation) to 1 (best overall match), with values near 0 representing neutral matches. More specialized degrees will have a wider range of match qualities, while the most general degrees will have match qualities clustered around 0.

2.1 Calculation of the Measure

The calculation of the measure proceeds in two steps. First, we estimate the earnings premium associated with each major-occupation pair. Second, we re-scale these premia to form our measure of match quality. Note that Step 1 does not control for differences in average earnings across occupations or across majors. In some applications it may be desirable to do one or both: here we present the simplest approach.

We estimate the major-occuapation premia using earnings data, combined with major and occupation categories. To improve the precision of our estimates, we also include individual characteristics that are known to be associated with earnings, and that are available in our data. We regress:

$$\ln(earn)_{i,m,o} = \alpha_0 + \sum_{m=1}^{n}\sum_{o=1}^{p} \beta_{m,o} D_{i,m,o} + X_i\Gamma + \text{year}_i + \epsilon_{i,m,o}, \tag{1}$$

where $\ln(earn)_{i,m,o}$ is the log of wage and salary income of individual i, graduate of major m, working in occupation o; $D_{m,o}$ is a dummy variable equal to 1 if individual i is a graduate from major m and working in occupation o (and 0 otherwise); the X_i includes gender, race/ethnicity, and a quadratic in potential experience; and $\epsilon_{i,m,o}$ is an error term. The set of $\hat{\beta}_{mo}$, the major-occupation earning premia, are our estimates of interest.

To calculate our measure of match quality, we first de-mean the major-occupation premia,[1] and then rescale the set to span (−1, 1). Specifically, we rescale by:

$$f(x) = \frac{2(x - \min)}{(\max - \min)} - 1 \tag{2}$$

1 This step is not necessary for calculating the match quality, but gives a natural meaning to the premia (which otherwise will be defined with respect to an arbitrary omitted category). These can be of interest in and of themselves, but more importantly it can be informative to compare the match qualities to the premia, as we do here.

where x is an estimated major-occupation premium and max and min are the largest and smallest values, respectively, in the set. This approach holds constant the proportional distance between major-occupation premia, while setting the upper bound (best match) to 1, and the lower bound (worst match) to −1.

3 Empirical Illustration

We illustrate our measure of match quality using data from the American Community Survey (survey waves 2009–2015). These data include detailed information on college major, along with occupation and income. We restrict our sample to individuals with a valid response for these three variables. Given our interest in linking labor market outcomes to education, we retain only college graduates between ages 25 and 35, who have typically completed their education but only have limited work experience. This leaves 841,516 observations.

Our measure requires that a premium be estimated for each major-occupation pair; there must therefore be a sufficient number of observations in each major-occupation cell. In this illustration we use a set of 14 majors and 11 occupations. Using these categories, our smallest cell has 44 observations, while the largest has 80,550.

Figure 1 shows the distribution of the resulting 154 match qualities (left panel), alongside the distribution of de-meaned major-occupation premia (right panel). Extreme values of match quality are the exception: the bulk of matches are closer to the middle of the distribution. This suggests that, for graduates of many majors, different occupations are not associated with substantially different relative earnings premia.

Tables 1 and 2 give some examples of major-occupation pairs and their match quality. Table 1 lists the five overall best matches, the five worst matches, and five matches from the middle of the distribution. The top match in this data set is Engineering/Architecture majors working in computer science occupations (by definition, scoring a match quality of 1). The worst match is Education majors working in service industries. Note that the Health/Nursing major shows up both on the list of best matches and on the list of worst matches. This wide variance of possible match outcomes makes Health/nursing a “specific” major (Leighton and Speer 2020).

Table 2 lists the best- and worst-matched occupations for each major. Note how variable the match quality measure is for the best match across majors: Engineering/Architecture and Computer Science have high scores for their top match, at 1.00 and 0.96, respectively. In contrast, the best-matched occupations for graduates from

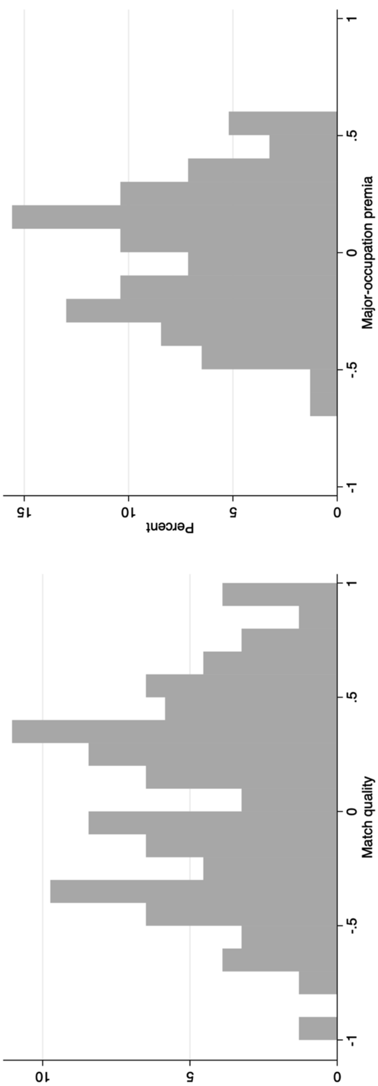

Figure 1: Distribution of match qualities and major-occupation premia. Authors' calculations from the ACS 2009–2015.

Table 1: Examples of best, median and worst matches overall.

Major	Occupation	Match quality
Best overall matches		
Engineering/architecture	Computer science	1.00
Engineering/architecture	Business and management	0.97
Computer science	Engineering/architecture	0.96
Health/nursing	Computer science	0.95
Engineering/architecture	Engineering/architecture	0.91
Median quality matches		
Communications/journalism	Editors/writers/performers	0.16
Humanities/liberal studies	Medical professionals	0.14
Health/nursing	Human/protective service/legal profess	0.13
Agriculture	Human/protective service/legal profess	0.12
Education	Educators	0.09
Worst overall matches		
Humanities/liberal studies	Service industries	−0.65
Education	Editors/writers/performers	−0.71
Health/nursing	Mechanics, laborers	−0.80
Health/nursing	Service industries	−0.92
Education	Service industries	−1.00

Authors' calculations from the ACS 2009–2015.

Education and Humanities/Liberal Studies score only 0.29 and 0.45 in match quality. The final column of Table 2 calculates the range of match qualities within that major. Health/Nursing has the highest range, at 1.87, while Agriculture has the lowest, at 0.95, followed closely by Communications/journalism. Majors with a narrow range of match qualities – never very well matched, nor very badly matched – are those defined as "general" majors in our prior paper (e.g. Agriculture, Communications), while the majors with a broad range of match qualities are what we call "specific" because they can be either very well matched or very badly matched. (e.g. Health/Nursing, Engineering).

Table 2: Best and worst occupational matches for each major.

Major	Worst match by major		Best match by major		
	Occupation	MQ	Occupation	MQ	Range
Agriculture	Administrative/clerical/legal support	−0.43	Computer science	0.52	0.95
Biological/interdisc sciences	Administrative/clerical/legal support	−0.57	Medical professionals	0.67	1.24
Business	Educators	−0.40	Business and management	0.75	1.15
Communications/journalism	Mechanics, laborers	−0.41	Business and management	0.57	0.98
Computer science	Educators	−0.47	Engineering/architecture	0.96	1.43
Education	Service industries	−1.00	Business and management	0.29	1.29
Engineering/architecture	Educators	−0.51	Computer science	1.00	1.51
Health/nursing	Service industries	−0.92	Computer science	0.95	1.87
Health/other	Service industries	−0.64	Computer science	0.63	1.27
Humanities/liberal studies	Service industries	−0.65	Business and management	0.45	1.10
Mathematics/physical sciences	Service industries	−0.34	Computer science	0.90	1.24
Social sciences	Service industries	−0.38	Business and management	0.65	1.03
Social work/protective serv	Service industries	−0.61	Engineering/architecture	0.55	1.16
Other	Service industries	−0.63	Computer science	0.38	1.01

MQ is the match quality measure. Authors’ calculations from the ACS 2009–2015.

4 Conclusion

In this note, we have presented a new approach to measuring the match quality between college major and occupation. While the logic of the measure is straightforward, a number of assumptions are embedded in its calculation. Researchers interested in applying the measure should consider carefully the set of majors and occupations to be used, and whether earnings premia ought to be normalized within major or occupation. Normalizing within majors could help address concerns of ability differences across entrants (or graduates) from different majors, while normalizing across occupations could average out cross-occupation wage differences which capture both productivity and non-pecuniary occupational amenities. Each approach has pros and cons; we present here the general case, with the expectation that it can be adapted as needed in future research.

Our measure also abstracts from the selection of individuals into majors, and from majors into occupations. Such selection is not random, and must be kept in mind when interpreting the major premia estimated in the way we have outlined here. Notwithstanding these considerations, this measure provides a new approach to an ongoing problem in labor economics: how to measure mismatch between field of study and occupation.

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