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It Pays to Study for the Right Job: Exploring the Causes and Consequences of the Education-Occupation Job Mismatch

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ABSTRACT

With the rapid increase in educational attainment, technological change, and greater job specialization, decisions regarding human capital investment are no longer exclusively about the quantity of education, but rather the type of education to obtain. The skills and knowledge acquired in specific fields of study are more valuable for some jobs compared to others, which suggests the existence of differences in the quality of the education-occupation match in the labor market. With this premise in mind, this paper aims to estimate the effect of the quality of this education-occupation job match on workers' wages and to explore the factors that contribute to the existence of such mismatch among workers with higher education (college or more). Using data from the American Community Survey 2010–16, we construct two indices that measure the quality of the education-occupation match: based on the predicted and observed distribution of workers using their fields of education and their jobs' occupation classification. Results suggest there is a wage gap of around 3–4 percent when comparing workers that have *good* job matches to those who have *bad* matches. Given the importance of the penalty for mismatched jobs, we find that structural characteristics such as unemployment, and individual characteristics such as gender, race, immigration status, and even homeownership affect the quality of horizontal mismatch as well as.

KEYWORDS: Educational Mismatch; Earnings; Wage Premiums; Educational Economics

JEL CLASSIFICATIONS: I21; J24; J31

1. INTRODUCTION

One of the main reasons to obtain a higher education degree is to use it to find a *good* job in the future. Peoples' human capital investments are made by planning ahead for the occupations they would like to have and the tasks they would like to do for a living. As Robst (2007a, 397) mentions, "one aspect of labor market success is the ability to utilize the investment in schooling in future employment." However, due to job market frictions, not all individuals end up in jobs that require the skills sets they acquired in their education. Due to a worldwide increase in educational attainment, technological changes, and greater job specialization, human capital decisions are no longer a question about the quantity of education to be acquired (e.g., a PhD versus a BA), but rather about the type or field of education that would better fit the labor market demand (e.g., economics vs. a medical degree), which suggests that the mismatch between education and occupation goes beyond the accumulation of human capital.

The literature has shown the education-occupation mismatch has implications for both employers and employees. Barron, Black, and Loewenstein (1989) posited that on-the-job training depends on a sorting mechanism performed by employers that assigns workers with different ability levels to positions that require different amounts of training: employers match the highest-ability workers to the positions that require the most training. More recently, Gavrel, Guironnet, and Lebon (2012) found that a poor match between a job and the worker caused by market imperfections increases the probability of the need for on-the-job training, which affects the employer through higher costs and loss of productivity. From an employee perspective, the skills and knowledge acquired in specific fields of study may make workers more productive in some jobs compared to others, which may be reflected through wages (Altonji, Arcidianono, and Maurel 2016; van der Werfhorst 2002). The literature also indicates that the quality of the job match can affect job satisfaction (Cabral 2005; Belfield and Harris 2002), which can have further impact on workers' wages and firms' productivity.

Using data from the American Community Survey 2010–16, we propose two indices of education-occupation match quality: based on the predicted and observed distribution of workers' higher education fields of study and their jobs' occupation classification. Using these

indices, we estimate the effect of the quality of this education-occupation job match over workers' wages and explore the factors that explain the quality of such match among workers with higher education degrees (college or more). Even though our research is focused solely on the quality of the education-occupation match effect over wages, the magnitude of this effect could help us to gain a better understanding of labor market dynamics for public policy reference, and serve as a guide to making informed higher education decisions.

The rest of the paper is organized as follows. Section 2 reviews the literature related to education-occupation mismatches. Section 3 describes the methodology used to calculate the match quality indices. Section 4 describes the data and summary statistics. Sections 5 and 6 present our results and analyze the job match wage premium and the factors that affect the education-occupation match. Section 7 concludes and discusses some public policy implications.

2. ABOUT THE EDUCATION-OCCUPATION MISMATCH

The education-occupation mismatch has been reviewed in the literature over the last several years under the concept of over- and undereducation. The idea was sketched initially by Eckhaus (1964) and Scoville (1966), who estimated the years of education required for an average functional performance in a given occupation (Halaby 1994). However, the concept was not formally used until Freeman (1976), who raised the topic as a problem of oversupply of workers with a college degree in the American economy during the 1970s. After them, substantial research has been performed using diverse data from around the world to analyze the effect of this phenomenon mainly over wages, but also over job satisfaction and the prevalence of on-the-job training.

In the literature, the education-occupation mismatch can be measured and understood using two different perspectives: vertical and horizontal education mismatch. The first, vertical mismatch, focuses on the quantity of education required for a job position and the quantity of education a worker brings to that job. The most common measure is the number of years of schooling (or level of education) above the number required for a specific job (Duncan and Hoffman 1981;

Rumberger 1987; Hersch 1991; Allen and van der Velden 2001). Using a vertical mismatch definition, a worker is considered overeducated (undereducated) if their level of education as measured through the number of years of schooling or degree surpasses (is lower than) the level of education his job requires. Through a meta-analysis based on 25 research studies about education mismatch in the United States and Europe, Groot and van den Brink (2000) found that the average incidence of overeducation using this definition is 13.1 percent and the incidence of undereducation is 9.6 percent, with overqualified workers earning a premium relative to the job but a penalty relative to their qualifications. As mentioned in Carolero and Pastore (2018), two opposite theories may explain overeducation (vertical mismatch): the first is a temporal market disequilibrium that goes against human capital theory but that restores to the equilibrium with time; and second, the job competition model, which reflects the accumulation of education that workers use to compete in the labor market.

On the other hand, as Sloane (2003) states, there would still be a mismatch if the *type* of education does not match even though the *level* of education does. This because by measuring overeducation through educational accumulation, the qualitatively distinct types of skills workers possess would be ignored, leading to the assumption that all workers with the same number of years of schooling are homogeneous and, thus, perfect substitutes (Halaby 1994). To overcome the problems this assumption would entail, the second perspective is “horizontal mismatch,” originally developed by Witte and Kalleberg (1995), which proposes that the educational returns are not fixed and depend on the opportunities individuals have to use their human capital.

Given its nature, horizontal mismatch is framed under assignment theory and focuses on the skills requirements of a job rather than on the quantity of education. Assignment theory allocates the most-skilled workers to the most-complex jobs and the least-skilled workers to the simplest jobs; then, the education-occupation mismatch occurs when the skills a worker has do not match with the skills required by their occupation.

In order to estimate the effect of a horizontal mismatch on labor market outcomes (such as wages), two types of measures can be used according to Groot and Massen van den Brink’s (2000) classification: subjective (self-reported) and objective (observational). Robst (2007a) was

the first to estimate the effect of the horizontal mismatch over wages using a subjective measure, namely, the worker's self-belief of how well their educational background relates to their actual occupation. He found for the United States that wages depend on the field of study, and also that workers with more general knowledge have a higher probability of mismatch (11.94 percent for male workers and 10.07 percent for female workers). More recently, Bender and Heywood (2009), focusing on doctorate recipients in the United States, found that academics with occupations reported as "not related to their education" have 13.8 percent lower wages than their counterparts. Nonacademics also suffer a wage penalty, but it is smaller, at 9.8 percent.

Regarding objective measures, Nordin, Persson, and Rooth (2010) were pioneers using of workers' fields of study to estimate the horizontal education-occupation mismatch. Using data from Sweden, they found there is a 20 percent wage penalty for male workers and 12 percent for female workers that are mismatched compared to others that have the same years of schooling, the same field of study, and also have a degree. For the United States, using data from the US Department of Labor's Occupational Information Network (O*NET) on individuals with postsecondary degrees in the 1980s and 1990s, Yakusheva (2010) found that, on average, individuals that matched their education to their occupations earn 30 percent higher wages than their counterparts. Yakusheva (2010) also classified individuals according to the relevance of their degrees for their occupations and found that those whose degree fields are unimportant for their occupations only have 6 percent higher wages than their counterparts and those whose degree fields are extremely important for their occupations show 21 percent higher wages.

Given that the measure used to quantify the education-occupation mismatch might affect the results (Nordin, Persson, and Rooth 2010), we rely on Ortiz and Kucel's (2008) statement that self-assessment information about workers' usage of knowledge at work has flaws due to the subjectivity of the measure. Because of that, we opted for an objective measure, such as the distribution of workers across their fields of study. This not only avoids using unreliable information, but also makes the results comparable with research that uses the same information. Nevertheless, as Lemieux (2014) describes, both objective and subjective measures tend to provide consistent results.

Recent studies, such as Marin and Hayes (2017), Montt (2017), and Lemieux (2014), analyze horizontal mismatch using workers' fields of study to understand the relationship between fields of study and specific occupations and to estimate the effect of a horizontal mismatch over different labor market outcomes, such as wages and job satisfaction. Even though these studies were performed using data from different countries, they all found that there is a link between certain occupations and specific fields of study and, when measured, that the horizontal mismatch has a negative effect over wages/earnings and job satisfaction. However, Montt (2017), using cross-country data, found that the wage penalty of the horizontal mismatch becomes relevant only when a vertical mismatch is also present.

Following this empirical framework, we estimate the effects of the quality of the education-occupation match over wages following assignment theory, which anticipates a loss of productivity caused by employers filling skilled positions with workers with different or lower skills¹—a dynamic that should be reflected in wages. There is evidence suggesting that a higher skill mismatch leads to lower labor productivity because of the less-efficient allocation of resources (McGowan and Andrews 2015).² As Sorenson and Kalleberg (1981) stated, under job-matching (assignment) theory, the most-skilled workers should occupy the most-skilled positions.

Nordin, Persson, and Rooth (2010) also point out that because of the nature of assignment theory—where workers and labor are matched according to their characteristics in the labor market—a worker's wage would be influenced not only by their own characteristics (such as education), but also the job's characteristics. Due to job allocation being the result of decision making aimed at maximizing utility (minimize costs) for both workers and employers, it must be noted that the distribution of workers among jobs is not random. Therefore, search costs play an important role in labor market decisions due to in the presence of uncertainty, as information is costly (McCall 1970).

¹ Sloane (2003) explains assignment theory as the assignment of heterogeneous workers in jobs with different complexity.

² Nevertheless, their conclusions are based on subjective mismatch measures.

3. MEASURING THE EDUCATION-OCCUPATION QUALITY MATCH

As described in the previous section, there are two methods for measuring the degree of relatedness or match quality between education and occupation. On the one hand, authors like Robst (2007a, 2007b) and Yuen (2010) use subjective measures, where people are asked their beliefs on whether or not their educational background is related to their jobs. On the other hand, Nordin, Persson, and Rooth (2010) and Marin and Hayes (2017) construct more objective measures of match quality, using information on the observed distribution of workers with different fields of study across occupations. Lemieux (2014) emphasizes that both types of measures yield similar results. The current paper takes an approach closer to Nordin, Persson, and Rooth (2010) by constructing two match quality indices based on the observed distribution of individuals across occupations and fields of study.

Assume a static labor market where the number of jobs available by occupation and number of workers with specific types of education are fixed and exogenous. Except for differences in educational background, all workers are identical and only look to maximize wages. All occupations hire and pay workers based on their productivity. Call N_i^o the total number of jobs available in a specific occupation i , N_j^F the total number of workers with field of degree j , and N the total number of people and jobs in the market. Under the assumption that markets clear and everyone can find a job we have:

$$\sum_{i \in OCC} N_i^o = \sum_{j \in fld} N_j^F = N \quad (1)$$

Without loss of generality, all terms in the above identity can be divided by N , so that it is written in terms of the relative size of the supply of jobs and workers:

$$\sum_{i \in OCC} p_o(i) = \sum_{j \in fld} p_F(j) = 1 \quad (2)$$

Where $p_O(i)$ is the proportion of workers in occupation i , and $p_F(j)$ is the proportion of workers with field of degree j . If all workers have the same skills and productivity levels regardless of their field of degree and all occupations pay the same wages, then there would be no assortative matching and, without an assignment problem, “finding a job would be reduced to locating a firm with a vacancy” (Sattinger 1993, 836). Firms would hire any type of worker for any type of occupation, and workers would be indifferent to which occupation to work at. In other words, after the market clears, the probability of finding a person with field of study j working for occupation i is random and would be defined as:

$$p_{OF}(occ = i, fld = j) = p_{OF}(i, j) = p_O(i) \times p_F(j) \quad (3)$$

Where $p_{OF}(i, j)$ is the probability of a person working in occupation i with a field of degree j . As described in the literature, the empirical and theoretical evidence suggests this is not the case. Field of study plays an important role in how workers are matched to jobs. Because different fields of study are likely to provide specific skill sets to workers and these skill sets are more valuable in specific occupations, it is likely that workers in specific fields of study are more often observed working in certain occupations.

In a frictionless labor market, this will create an automatic attraction between specific occupations and workers with specific fields of education, with workers seeking to maximize their wages given their set of skills and employers hiring the most productive workers for a given occupation. Evidence of this is that one observes a high concentration of lawyers working as legal professionals but not as journalists (Nordin, Persson, and Rooth 2010).

Since the total number of jobs per occupation and total labor supply by field of study are fixed, even with full job mobility with zero frictions, not all workers would be able to work in the occupation that is the most related to their field.³ This implies that there are limits regarding the minimum and maximum number of people with field of study j that could work in occupation i . The maximum concentration of education-occupations pairs would be observed for those

³ Although less likely, there is also the scenario where some workers may not be able to avoid working for their least-preferred occupational choice.

combinations where the occupations are the most related to the field of study, whereas those combinations that are the least related would probably not be observed.

These maximum and minimum expected concentrations, or bounds, are defined by the Frechet Inequalities or Frechet Bounds (Frechet 1935):

$$\max(0, p_O(i) + p_F(j) - 1) \leq p_{OF}(i, j) \leq \min(p_O(i), p_F(j)) \quad (4)$$

These two cases describe scenarios where everyone works for the job most related to their field of study (second case), or no one does and jobs are assigned at random (first case). For most scenarios, however, due to frictions in the labor market and the presence of other factors that both workers and employers may consider at the time of hiring, the extreme scenarios described above are not likely to be observed. Nevertheless, under the assumption that, on average, individuals with field of education j prefer to work in occupation i because they believe that occupation is the best match for their skill set, the above points of reference can be used to create indices of education-occupation match quality (I_{MQ}).

The first index (I_{MQ}^1) uses the ratio of the observed proportion of workers with education j in occupation i , divided by the expected proportion under the assumption of no assortative matching:

$$I_{MQ}^1(i, j) = \frac{p_{OF}(i, j)}{p_O(i) \times p_F(j)} \quad (5)$$

With higher values of the index suggesting that the workers with occupation i and field of degree j have a better match, compared to the benchmark of no assortative matching or random matching.

The second index (I_{MQ}^2) uses the Frechet bounds to assess, given the observed distribution of fields of bachelor's degree and occupations, how large is the concentration of workers compared to the highest and lowest expected concentrations:

$$I_{MQ}^2(i, j) = \frac{p_{OF}(i, j) - \max(0, p_O(i) + p_F(j) - 1)}{\min(p_O(i), p_F(j)) - \max(0, p_O(i) + p_F(j) - 1)} \quad (6)$$

In this case, the closer $p_{OF}(i, j)$ is to theoretical maximum, the better is the quality of the match and vice versa.

These two indices are similar in spirit to the categorization used in Nordin, Persson, and Rooth (2010), where fields of study and occupation pairs are classified as matched, weakly matched, or mismatched based on overall density and also on somewhat arbitrary criteria for weakly matched and mismatch cases (Nordin, Persson, and Rooth 2010, 1050). In contrast, the indices proposed here do not depend on any subjective criteria. As it will be described in the data section, monotonic transformations of our indices are used for the rest of the analysis.

4. DATA AND SUMMARY STATISTICS

Data for this paper was taken from the American Community Survey (ACS), obtained from the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al. 2017). The ACS is the largest ongoing national survey in the United States, collecting data from 3.5 million households each year since 2005, replacing the decennial census's long form.

While data on educational attainment has been collected as part of the ACS since 2005, detailed information regarding fields of bachelor's degree was not collected until 2009. In specific, all people who participate in the survey and have at least a bachelor's degree were asked to specify the major of their bachelor's degree, even if they had a higher education degree, such as a master's or PhD. While persons in the survey could provide multiple answers regarding their fields of bachelor's degree, the information in the ACS data provides details of the first two fields reported on the survey form. In 2010, the census codes used for the classification of fields of bachelor's degree changed, and this is the reason why we use data from 2010 on—to maintain a consistent classification.

Since the aim of the paper is to analyze the quality of the education-occupation match for the core of the labor force in the United States, only individuals between 25 to 64 years of age with at least a BA degree are included in the analysis. Because information regarding occupation is not available for individuals who have never worked or have been unemployed for longer than five years, they were excluded from the sample. Nevertheless, we include in the sample the information on individuals who are currently unemployed, but where the information on their last occupation is available.

In order to obtain the most accurate measures possible, the estimation of our indices of education-occupation match quality uses pooled data for the years 2010 to 2016. This gives us a sample of 3,387,509 observations. For the estimation of the indices, the proportions of people by occupation and field of bachelor's degree are calculated using simple weighted data. For the construction of the matching quality indices (I_{MQ}^k) we used the detailed fields of bachelor's degree (173 fields) and detailed occupation categories (453 occupations), but estimations using more aggregated categorizations are also performed for robustness (using 37 fields of bachelor's degree and 26 occupation categories).

Since approximately 10 percent of the sample declared a second field of bachelor's degree, the indices described in the previous section were modified. The indices were constructed based on observing a specific field of bachelor's degree as the first or second answer provided. The indices then become:

$$I_{MQ}^1(i, j) = \frac{p_{OF}(i, f_1 = j | f_2 = j)}{p_O(i) \times p_F(f_1 = j | f_2 = j)}, \text{ and} \quad (7)$$

$$I_{QM}^2(i, j) = \frac{p_{OF}(i, f_1 = j | f_2 = j) - \max(0, p_O(i) + p_F(f_1 = j | f_2 = j) - 1)}{\min(p_O(i), p_F(f_1 = j | f_2 = j)) - \max(0, p_O(i) + p_F(f_1 = j | f_2 = j) - 1)} \quad (8)$$

Since these indices have a skewed distribution, for the purposes of the analysis, a monotonic transformation is applied:

$$F_k(i, j) = \frac{\ln(I_{MQ}^k(i, j)) - E(\ln(I_{MQ}^k(i, j)))}{Var[\ln(I_{MQ}^k(i, j))]^{0.5}} \text{ for } k = 1, 2 \quad (9)$$

where the mean and standard deviation are estimated using weighted pooled data for 2010–16. The transformed indices $F_k(i, j)$ are z-scores that preserve the interpretation as before.

For the econometric analysis, we focus on data for 2016 only. In addition to the sample restrictions set above, other restrictions were applied. Workers with any reported self-employment income or those who worked for fewer than 40 weeks last year were excluded from the sample. Individuals identified as roommates/housemates and nonrelatives were also excluded from the sample. Similar to Robst (2007a), the log of annual wage income is used as a dependent variable in the wage analysis, and our index of match quality for analysis is what determines whether the job is well matched or not.

The index of match quality is assigned to each person in the sample based on their field of bachelor’s degree and occupation classification. For individuals with two fields for bachelor’s degree, the field/occupation that suggests the best match (highest index) of the two associated indices is assigned, and the corresponding field of bachelor’s degree is kept for analysis.⁴

4.1 Summary Statistics

The two constructed indices are highly correlated. Using the weighted 2016 subsample, after the indices are assigned to workers, they have a correlation of 0.8. To illustrate how correlated the two indices are, in table 1, a contingency table is presented where individuals are classified in four groups—mismatch (./-1), weak mismatch (-1/0), weak match (0/1), and match (1/.)—based on the value of the standardized indices. It should be noticed that because a standardized index is used, the classification used in table 1 is in relative terms to all other workers and occupations observed between 2010 and 2016. In other words, what could be considered as a “good match” between field of study and occupation based on the proposed indices could fall into the “weak match” group under Nordin, Persson, and Rooth’s (2010) classification.

⁴ The same process is used for assigning the matching index when using the aggregated occupation and field of degree classifications.

The results in table 1 suggest both indices provide rather consistent classifications. No one that is classified as a mismatch or weak mismatch based on index 1 is classified as matched with respect to index 2. In contrast, there are a few observations (fewer than 2 percent) that indicate a particular education-occupation combination is mismatched based on index 2 and classified as matched based on index 1. Looking closely at the group with the largest disagreement, it is possible to find cases where both classifications make sense. For example, someone in the mechanical engineering major (field of bachelor’s degree) working as “materials engineer” (occupation) seems to be correctly classified as “matched” based on index 1, whereas an agricultural economist major employed as an extraction worker might be better classified as a mismatch, as in index 2.

Table 1. Contingency Table: Education-Occupation Match Quality

Index MQ 2		-9/-1	-1/0	0/1	1/9	
Index MQ 1		Mismatch	Weak mismatch	Weak match	Match	Total
-9/-1	Mismatch	7.173	4.885	0.000	0.000	12.058
-1/0	Weak mismatch	7.327	24.851	14.836	0.000	47.014
0/1	Weak match	0.996	3.857	13.520	4.799	23.172
1/9	Match	0.039	0.807	3.843	13.066	17.755
Total		15.535	34.400	32.199	17.865	100

Note: Classifications are based on the standardized matching quality indices. Proportions are estimated using survey weights for the 2016 final sample.

The results from table 1 suggest that neither of the two indices is infallible. However, it suggests that they both are able to capture different dimensions that correlate to a better job match. For this reason, through the rest of the paper both indices are used to show how robust the links are between earnings and match quality.

To show the differences in classification, each index provides a list of 10 random fields of bachelor’s degrees with the best and worst occupation match based on both indices shown in table 2.⁵ The results are mostly consistent across both indices’ classifications, although some of the classifications are somewhat questionable. For example, for humanities majors the best occupation match (*B*) based on index 1 is telemarketer, which is rather debatable, while elementary and middle-school teacher (I_{MQ}^2) seems more appropriate. In contrast, it seems more

⁵ The complete list of occupation–field of degree match ranks is available upon request.

appropriate to classify physiologists as chiropractors (I_{MQ}^1) rather than as physicians and surgeons (I_{MQ}^2).

It should be noticed that even working with the 2010–16 ACS pooled data, using detailed occupation and field of bachelor’s degree categories puts a lot of strain on the data. Indices of match quality between fields of bachelor’s degree and occupations that are greatly underrepresented in the data are likely get a spuriously large value in the index of quality match. One example of this problem is that, based on index 1, people with a field of degree in “business management and administration” find their best occupational match as “automotive service technicians and mechanics.” This particular occupation is underrepresented in the data, with only 0.03 percent of the observations in the sample employed in this occupation. To account for this potential problem, robustness checks using more aggregated occupation and field of degree classifications are applied and additional restrictions are imposed on the data in the econometric analysis.

Table 2. Sample of Field of Degree with Best and Worst Education-Occupation Match

Field of Degree	Index MQ 1	Index MQ 2
Agricultural economics	<i>W</i> : Designers <i>B</i> : Buyers and purchasing agents of farm products	<i>W</i> : First-line enlisted military supervisors <i>B</i> : Farmers, ranchers, and other agricultural managers
General education	<i>W</i> : Electrical and electronics engineers <i>B</i> : Elementary and middle-school teachers	<i>W</i> : Electrical and electronics engineers <i>B</i> : Elementary and middle-school teachers
General engineering	<i>W</i> : Occupational therapists <i>B</i> : Civil engineers	<i>W</i> : Occupational therapists <i>B</i> : Civil engineers
Humanities	<i>W</i> : Environmental scientists and geoscientists <i>B</i> : Telemarketers	<i>W</i> : Environmental scientists and geoscientists <i>B</i> : Elementary and middle-school teachers
Genetics	<i>W</i> : First-line supervisors of sales workers <i>B</i> : Biological scientists	<i>W</i> : Heating, air conditioning, and refrigeration mechanics <i>B</i> : Physicians and surgeons
Physiology	<i>W</i> : Civil engineers <i>B</i> : Chiropractors	<i>W</i> : Purchasing agents, except wholesale, retail, and farm products <i>B</i> : Physicians and surgeons
Political science and government	<i>W</i> : Occupational therapists <i>B</i> : Lawyers, judges, magistrates, and other judicial worker	<i>W</i> : Occupational therapists <i>B</i> : Lawyers, judges, magistrates, and other judicial worker
Sociology	<i>W</i> : Atmospheric and space scientists <i>B</i> : Social workers	<i>W</i> : Atmospheric and space scientists <i>B</i> : Social workers
Accounting	<i>W</i> : Medical scientists and life scientists. <i>B</i> : Accountants and auditors	<i>W</i> : Medical scientists and life scientists. <i>B</i> : Accountants and auditors
Finance	<i>W</i> : Astronomers and physicists <i>B</i> : Credit analysts	<i>W</i> : Astronomers and physicists <i>B</i> : Credit analysts

Note: Best (B) and worst (W) education-occupation match are based on constructed indices. Fields were chosen at random.

Table 3 provides a summary of selected demographic statistics, based on both match quality indices and using the match/mismatch classification from table 1. Looking at the average annual wage income, both indices suggest that jobs with a better education-occupation match earn higher wages, with the only exception of workers with a weak match classification based on index 2. Similarly, people who work in a better job match are also more likely to work in occupations that employ a larger share of college-educated workers (percent of BA in occupation),⁶ a rough measure of vertical education match.

Regarding other characteristics, the summary statistics suggest that younger workers, married individuals, and white workers seem to be more likely to work in better-matched jobs. No clear trends are observed regarding other statistics.

Table 3. Summary Statistics of Selected Demographics by Quality of Match

	Index MQ 1				Index MQ 2			
	Mismatch	Weak mismatch	Weak match	Match	Mismatch	Weak mismatch	Weak match	Match
Annual wage income	80,302	82,492	86,753	93,919	77,851	81,502	92,800	85,261
Usual hours of work per week	42.4	42.9	43.5	42.5	42.3	42.7	43.7	42.4
% of BA in occupation	64.7%	50.1%	68.9%	71.7%	51.9%	53.4%	60.7%	78.5%
25–34 years old	24.4%	27.4%	29.2%	32.0%	28.1%	28.1%	27.4%	30.4%
35–44 years old	28.6%	27.6%	28.1%	27.5%	27.8%	27.5%	27.9%	28.1%
45–54 years old	26.7%	26.3%	25.6%	23.2%	24.7%	26.1%	26.5%	23.9%
55–64 years old	20.3%	18.8%	17.2%	17.3%	19.4%	18.4%	18.2%	17.5%
Men	46.4%	50.9%	46.6%	48.6%	51.7%	50.3%	53.1%	36.5%
Women	53.6%	49.1%	53.4%	51.4%	48.3%	49.7%	46.9%	63.5%
Married	64.7%	62.7%	66.2%	67.0%	62.7%	62.7%	65.5%	68.0%
Single	21.0%	23.8%	21.9%	21.4%	23.9%	24.1%	21.9%	19.9%
Other	14.3%	13.5%	11.9%	11.6%	13.4%	13.3%	12.7%	12.2%
Native-born citizen	82.0%	84.1%	84.5%	81.0%	81.6%	83.2%	83.9%	84.4%
Naturalized citizen	11.7%	9.7%	9.1%	12.4%	11.5%	10.2%	9.7%	10.6%
Immigrant	6.3%	6.1%	6.4%	6.7%	7.0%	6.6%	6.3%	5.0%
White	68.6%	70.5%	72.8%	71.0%	68.9%	70.4%	71.2%	73.1%
Black	9.8%	9.3%	7.9%	7.4%	9.3%	8.9%	8.7%	7.6%
Hispanic	8.5%	8.7%	8.0%	6.8%	8.7%	8.5%	8.4%	6.8%
Other	13.0%	11.5%	11.4%	14.8%	13.1%	12.2%	11.7%	12.4%

Note: Based on the 2016 ACS, using sample weights. The matching categories are constructed using the standardized indices and the following criteria: mismatch (-1/0), weak mismatch (-1/0), weak match (0/1), and match (1/1).

⁶ The share of workers with at least a bachelor's degree by detailed occupation categories was constructed using the pooled 2010–16 ACS data for all individuals between 25–64 years old.

5. RESULTS

5.1 Education-Occupation Mismatch and the Wage Premium

In order to formally analyze the wage income penalty associated with job match quality, standard Mincer-type income equations are estimated. Since the ACS only has information on annual income, the logarithm of annual wage income is used as the dependent variable; however, to better account for the heterogeneity of weeks and hours worked last year, the data is constrained to people who worked at least 40 weeks last year, and the log of usual hours of work per week is included as control.

In addition to the standard demographic characteristics—such as age, civil status, immigration status, and race—detailed information on educational attainment above a bachelor’s degree, the presence of any serious disability,⁷ and English-speaking ability⁸ are also included as proxies for skill. In order to control for unobserved regional differences, such as costs of living and labor market conditions, state fixed effects are included in the specification. Finally, the indices of match quality are included as the main controls. The results from this baseline model are presented in columns 1 and 2 of table 4, with robust standard errors reported.

The results of this specification are as expected, with sizable wage differences due to age, sex, and race, and with somewhat small but statistically significant wage differences by immigration status. Regarding the skill variables, people with reported disabilities earn wages that are about 15 percent lower and those who lack English language ability are heavily penalized, with a wage penalty of almost 40 percent for those indicating they do not speak English well. Finally, possessing a graduate degree provides a large boost to wages, and this seems to be the highest for people with a professional degree (50 percent higher wage).

In this specification, both match quality measures have a large and statistically significant impact on wages, with similar magnitudes. A one standard-deviation increase in the quality of the job

⁷ This is a dummy that takes the value of one if the interviewee indicates having any type of difficulty regarding self-care, vision, hearing, independent living, or any kind of ambulatory or cognitive disability.

⁸ Individuals who do not speak English at work are asked to assess how well they speak English.

match increases wages between 6.5–7.3 percent.⁹ Considering that the median wage for workers in the sample is \$65,000 per year, working a job that is a better education-occupation match (one standard-error higher index) would imply a \$4,225 wage premium per year. While the estimate is not fully comparable with previous studies in the literature, the estimations are somewhat similar to those reported in Robst (2007a; 2007b, 2008), Nordin, Persson, and Rooth (2010), Allen and van der Velden (2001), and Lemieux (2014).

One aspect that is not accounted for in columns 1 and 2 of table 4 is that the estimated results could be driven by the fact that some occupations demand highly educated workers and thus pay higher wages, and that individuals in high-paying fields are also more likely to work for jobs that are highly related to their educational background (Altonji, Arcidiacono, and Maurel 2016).¹⁰ It must be noted that the labor market payoff differs according to the field of study chosen (even controlling for institutions and peer quality) because individuals choose those fields of study where they have a comparative advantage (Kirkeboen, Leuven, and Mogstad 2016).

To address this concern, columns 3 and 4 of table 4 provide the results of the baseline model, including detailed occupation fixed effects. In columns 5 and 6, the models are again reestimated, adding field of education fixed effects. After adding the occupation fixed effects, the wage gaps associated with most of the demographic characteristics and skill proxies shrink. Only the coefficients for foreign-born noncitizens seem to become more negative after including the occupation fixed effect. Adding field of study fixed effects as controls further shrinks the magnitude of the estimated coefficients, but the changes are smaller. In terms of the job matching quality index, the point estimates are reduced by half, but remain statistically significant at the 1 percent level of confidence. Under this specification, a one standard-deviation improvement in the job match quality would imply a wage increase between 2.86–3.01 percent, or \$1,950 per year for the median worker.

⁹ The percentage effects were estimated as follows: $\%change = \exp(b) - 1$. For example, a coefficient of 0.07 translates into a percentage change of 7.3 percent.

¹⁰ As an example, Altonji, Arcidiacono, and Maurel (2016) use STEM majors, which has a larger causal effect over productivity but tends to be less appealing for students.

Table 4. Wage Equation Results: Dependent Variable Log of Annual Wage Income

	(1)	(2)	(3)	(4)	(5)	(6)
Age groups						
35–44 years old	0.2275* [0.0033]	0.2238* [0.0033]	0.2174* [0.0030]	0.2164* [0.0030]	0.2167* [0.0030]	0.2166* [0.0030]
45–54 years old	0.3005* [0.0035]	0.2948* [0.0035]	0.2868* [0.0032]	0.2851* [0.0032]	0.2808* [0.0032]	0.2807* [0.0032]
55–64 years old	0.2695* [0.0039]	0.2646* [0.0039]	0.2738* [0.0036]	0.2719* [0.0036]	0.2711* [0.0036]	0.2708* [0.0036]
Women	-0.2424* [0.0027]	-0.2527* [0.0027]	-0.1598* [0.0026]	-0.1607* [0.0026]	-0.1438* [0.0027]	-0.1438* [0.0027]
Civil status (married)						
Single	-0.1398* [0.0034]	-0.1361* [0.0034]	-0.1109* [0.0031]	-0.1104* [0.0031]	-0.1079* [0.0031]	-0.1078* [0.0031]
Other	-0.0850* [0.0040]	-0.0638* [0.0040]	-0.0638* [0.0036]	-0.0642* [0.0036]	-0.0617* [0.0036]	-0.0618* [0.0036]
Neither head nor spouse	-0.3002* [0.0053]	-0.3015* [0.0053]	-0.2010* [0.0049]	-0.2021* [0.0049]	-0.2004* [0.0049]	-0.2008* [0.0049]
Immigration status						
Foreign-born citizen	0.0145+ [0.0058]	0.0176* [0.0058]	0.0035 [0.0052]	0.0041 [0.0052]	-0.0114+ [0.0052]	-0.0112+ [0.0052]
Foreign-born noncitizen	-0.0344* [0.0073]	-0.0293* [0.0073]	-0.0442* [0.0066]	-0.0432* [0.0066]	-0.0662* [0.0066]	-0.0660* [0.0066]
Race						
Black	-0.1345* [0.0049]	-0.1366* [0.0048]	-0.0840* [0.0045]	-0.0852* [0.0045]	-0.0836* [0.0045]	-0.0836* [0.0045]
Hispanic	-0.1213* [0.0058]	-0.1239* [0.0058]	-0.0664* [0.0053]	-0.0676* [0.0053]	-0.0648* [0.0053]	-0.0650* [0.0053]
Other	0.0448* [0.0052]	0.0446* [0.0052]	-0.0073 [0.0047]	-0.0078^ [0.0047]	-0.0140* [0.0047]	-0.0143* [0.0047]
Education level						
Master degree	0.1480* [0.0027]	0.1446* [0.0027]	0.1373* [0.0027]	0.1380* [0.0027]	0.1356* [0.0027]	0.1356* [0.0027]
Professional degree	0.4428* [0.0060]	0.4432* [0.0060]	0.1883* [0.0071]	0.1891* [0.0071]	0.1896* [0.0071]	0.1897* [0.0071]
PhD degree	0.2959* [0.0064]	0.3029* [0.0064]	0.2433* [0.0068]	0.2450* [0.0068]	0.2413* [0.0069]	0.2414* [0.0069]
Any disability	-0.1503* [0.0070]	-0.1487* [0.0070]	-0.1060* [0.0063]	-0.1059* [0.0063]	-0.1022* [0.0062]	-0.1025* [0.0062]
Speaking ability						
Yes, speaks very well	-0.0211* [0.0052]	-0.0197* [0.0052]	-0.0260* [0.0047]	-0.0256* [0.0047]	-0.0305* [0.0047]	-0.0304* [0.0047]
Yes, speaks well	-0.2843* [0.0097]	-0.2789* [0.0096]	-0.1848* [0.0086]	-0.1845* [0.0086]	-0.1898* [0.0085]	-0.1902* [0.0085]
Yes, but not well	-0.5025* [0.0174]	-0.4962* [0.0174]	-0.2673* [0.0152]	-0.2689* [0.0152]	-0.2682* [0.0154]	-0.2689* [0.0154]
Index MQ 1	0.0637* [0.0012]		0.0334* [0.0012]		0.0286* [0.0013]	
Index MQ 2		0.0700* [0.0012]		0.0343* [0.0013]		0.0301* [0.0014]
Detailed occupation fixed effects			X	X	X	X
Detailed field of degree fixed effects					X	X
Observations	383554	383554	383552	383552	383552	383552
Adjusted R ²	0.390	0.391	0.509	0.509	0.514	0.514

Note: ^ p<0.1, + p<0.05, * p<0.01. Robust standard errors are reported in brackets. All models include controls for number of weeks worked, log of usual hours worked per week, and state fixed effects.

5.2 Robustness to Measurement Errors

As described in the data section, one of the drawbacks of the methodology used for the construction of the match quality indices is that they are prone to measurement errors in underrepresented occupations or fields of study. In this case, small changes to the numerator will have a large influence on an individual's match quality index, making it seem that a random occurrence of a specific education-occupation match is a good match when it is not.

To address this potential problem, table 5 provides a few robustness checks using the same specification as in table 4. Row 1 provides estimates using a more aggregated occupation classification, reducing the number of occupation fixed effects from 439 to 26 occupations.¹¹ Row 2, in addition to using an aggregated occupation classification, provides estimates using aggregated field of study classifications, reducing the dimension from 173 detailed fields of study to 37. These changes in the specification have a small impact on the previously described estimates, increasing the wage premium from 3 percent to almost 4.5 percent, but otherwise remaining consistent with the main results.

In rows 3–5, the data is restricted to exclude extreme observations with extreme values that could be spuriously affecting the estimations: in row 3, occupations that represent less than 0.05 percent of the sample are excluded; in row 4, occupations where less than 10 percent of workers have a college degree are excluded; and finally, in row 5, observations at the top and bottom 0.5 percent (based on the index of matching quality) are excluded. None of these restrictions have any impact on the estimated wage premium associated with better matching quality.

¹¹ The detailed occupation classification corresponds to the harmonized occupation coding scheme based on the US Census Bureau's 2010 ACS occupation classification scheme; the aggregated occupation coding is based on standard reclassification.

Table 5. Robustness on Matching Quality and Earnings

	(1) Index MQ1		(2) Index MQ2	
<i>1: Specification: IMQ based on detailed field of degree fixed effects, aggregated occupation</i>				
Index MQ	0.0391*	[0.0013]	0.0442*	[0.0015]
N	383554		383554	
<i>2: Specification: IMQ based on aggregated field of degree fixed effects, aggregated occupation</i>				
Index MQ	0.0391*	[0.0013]	0.0379*	[0.0015]
N	383554		383554	
<i>3: Sample restriction: Excluded, occupation share < 0.05 percent</i>				
Index MQ	0.0285*	[0.0013]	0.0300*	[0.0015]
N	372143		372143	
<i>4: Sample restriction: Excluded, occupations with fewer than 10 percent college-educated workers</i>				
Index MQ	0.0278*	[0.0013]	0.0295*	[0.0015]
N	369135		369135	
<i>5: Sample restriction: Excluded, top and bottom 0.5 percent based on IMQ</i>				
Index MQ	0.0315*	[0.0014]	0.0307*	[0.0015]
N	378375		381341	

Note: Standard errors in brackets: $\hat{p} < 0.1$, $^+ p < 0.05$, $^* p < 0.01$. Uses the same specification as in table 4. Index of matching quality (IMQ).

5.3. Heterogeneity

As shown in Nordin, Persson, and Rooth (2010), the impact of being in a mismatched job on earnings is different for men compared to women. In a similar way, such heterogeneity might be present across other key demographics like age, race, and immigration status. To test this hypothesis, a simplified strategy is used where each of the indices of match quality is interacted with the demographic of interest, keeping the rest of the specification the same as in the preferred model (table 4, column 5 for I_{MQ}^1 and 6 for I_{MQ}^2). These results are presented in table 6.

Looking at the interaction between the indices of match quality and age group, the results indicate that people from all age ranges receive a positive wage premium when working in a job that matches with their education. The estimations suggest that people between the ages of 25–34 (baseline group) receive a wage premium of about 2.7 percent for a one standard-deviation improvement in the index of matching quality. While no statistically significant difference was observed for people ages 35–44, those between the ages of 45–54 receive a wage premium that is 18 percent larger compared to the baseline group. Those between 55–64 years of age have an even higher wage gap compared to the baseline group that varies from 36.3 percent (I_{MQ}^1) to 39.2 percent (I_{MQ}^2). As we will show later, these results could be explained by an increase in the

likelihood of mismatch with age, which could lead to a higher wage premium for those who are matched. Furthermore, as pointed out in Bender and Heywood (2009), the wage premium for working in a well-matched job may improve across time as these workers continue to specialize compared to workers that were matched in a bad job. This makes it reasonable to expect that mismatched workers face a larger wage penalty in the later years of their careers.

About gender, the interaction regarding earnings provides results somewhat different from those described in the literature. Robst (2007b) shows that, in general, the wage penalty for working in a mismatched job is somewhat larger for men (10.2 percent) than for women (8.9 percent). Nordin, Persson, and Rooth (2010) also found that the earnings penalty for working in a mismatched job is higher for men (19.5 percent) compared to women (12.2 percent) after controlling for fields of study. The estimations presented here, however, suggest that the wage premium for working in a better-matched job is between 32.5 percent (I_{MQ}^2) and 56.6 percent (I_{MQ}^1) larger for women compared to men. Our results are comparable to those of Bender and Heywood (2009) who found that female PhD graduates are affected by horizontal mismatch more severely than men. Even though they used a subjective measure, they found that women have earnings gains caused by horizontal mismatch that are 22.6 percent greater than men if the mismatch was caused by the desire for better pay or a promotion; however, if the cause of the mismatch was family reasons, women could suffer a wage penalty that is 55.9 percent greater than men.

Turning next to the interactions with race and immigration status, the results indicate that whites and native-born citizens (baseline group) get the lowest payoff for working in a job with a better match to their field of studies. In comparison, all other races obtain payoffs that are between 22.2 percent (Other I_{QM}^2) to 64 percent (Hispanic I_{QM}^1) greater than the ones observed for whites. In a similar fashion, the added payoff that foreign-born citizens get is between 45.8 percent (I_{MQ}^2) to 62.5 percent (I_{MQ}^1) larger than native-born citizens (baseline group). No statistical difference is observed for noncitizen immigrants. This could be attributed to a “favorably selectivity among migrants,” which is explained by Chiswick and Miller (2009, 9) as a combination of a demand for highly skilled immigrants (that are granted visas) and self-selection. Given that immigrants with citizenship may have chosen to move to the United States based on their occupation

preferences, it would be logical to expect that they would get higher wages when properly matched compared to native-born workers.

Table 6. Job Match Quality: Heterogeneity for Selected Characteristics

	Index MQ 1		Index MQ 2	
<i>Age</i>				
Index MQ	0.0267*	[0.0020]	0.0273*	[0.0021]
Index MQ x (35-44 yrs)	-0.0038	[0.0027]	-0.0013	[0.0027]
Index MQ x (45-54 yrs)	0.0050 [^]	[0.0028]	0.0049 [^]	[0.0028]
Index MQ x (55-64 yrs)	0.0097*	[0.0030]	0.0107*	[0.0031]
<i>Gender</i>				
Index MQ	0.0221*	[0.0018]	0.0258*	[0.0019]
Index MQ x female	0.0125*	[0.0022]	0.0084*	[0.0023]
<i>Race</i>				
Index MQ	0.0250*	[0.0014]	0.0270*	[0.0015]
Index MQ x black	0.0114*	[0.0042]	0.0102 ⁺	[0.0042]
Index MQ x Hispanic	0.0160*	[0.0045]	0.0152*	[0.0045]
Index MQ x other	0.0111*	[0.0033]	0.0080 ⁺	[0.0034]
<i>Immigration Status</i>				
Index MQ	0.0272*	[0.0013]	0.0286*	[0.0015]
Index MQ x immigrant citizen	0.0170*	[0.0036]	0.0145*	[0.0037]
Index MQ x immigrant noncitizen	-0.0082	[0.0051]	-0.0013	[0.0052]

Note: Standard errors in brackets. [^] $p < 0.1$, ⁺ $p < 0.05$, * $p < 0.01$. Uses the same specification as in table 4.

6. EXPLAINING THE JOB MATCH

The empirical results provided in the previous sections suggest there is a payoff for working a job that is a good match between a worker's educational background and the requirements demanded by an occupation. This raises a question: If working in a better-matched job has, on average, a positive impact on wages, why are there individuals working for jobs that offer a less-than-ideal match? In other words, are there any factors that explain why people work in jobs with a lower match quality? To explore this question, ordinary least square (OLS) models are estimated using a specification similar to the one used for the wage equation model (excluding

the variables related hours of work), and using both our indices of match quality as dependent variables. The results are presented in table 7.

Following the literature, detailed field of education fixed effects are included as controls in all models to account for people choosing specific fields of education because of the higher earning potential those fields have. In addition, because individuals may also choose to work in better-paid occupations even if those occupations are less related to their fields of education, controls for detailed occupation fixed effects are also included in the specification. In this sense, any effect we were to find with respect to other demographic characteristics would be related to behavioral decisions abstracting from the idiosyncratic preferences for specific occupations or fields of study.

Table 7. Exploring the Determinants of Education-Occupation Match

	(1)		(2)	
	Index MQ1		Index MQ2	
<i>Age</i>				
35–44 years old	-0.0758*	[0.0049]	-0.0655*	[0.0043]
45–54 years old	-0.0908*	[0.0050]	-0.0780*	[0.0044]
55–64 years old	-0.1136*	[0.0054]	-0.0951*	[0.0047]
<i>Gender</i>				
Female	-0.0225*	[0.0039]	-0.0206*	[0.0035]
<i>Civil status (married)</i>				
Single	0.0183*	[0.0047]	0.0136*	[0.0042]
Other	-0.0129 ⁺	[0.0054]	-0.0090 [^]	[0.0048]
Children or other	-0.0939*	[0.0074]	-0.0768*	[0.0066]
<i>Immigration status</i>				
Foreign-born citizen	-0.0104	[0.0077]	-0.0073	[0.0068]
Foreign-born noncitizen	-0.0039	[0.0093]	0.0023	[0.0082]
<i>Race</i>				
Black	-0.0521*	[0.0070]	-0.0481*	[0.0063]
Hispanic	-0.0040	[0.0074]	-0.0020	[0.0065]
Other	-0.0304*	[0.0068]	-0.0226*	[0.0060]
<i>Education level</i>				
Master degree	-0.0238*	[0.0041]	-0.0191*	[0.0037]
Professional degree	-0.0376*	[0.0110]	-0.0363*	[0.0097]
PhD degree	0.0111	[0.0106]	0.0133	[0.0094]
<i>Disability</i>				
Any disability	-0.0488*	[0.0093]	-0.0427*	[0.0082]
<i>English-speaking ability</i>				
Yes, speaks very well	-0.0098	[0.0069]	-0.0087	[0.0061]
Yes, speaks well	-0.0915*	[0.0119]	-0.0721*	[0.0105]
Yes, but not well	-0.2373*	[0.0202]	-0.1912*	[0.0179]
Observations	383583		383583	

Note: Standard errors in brackets: [^] $p < 0.1$, ⁺ $p < 0.05$, * $p < 0.01$. The specification follows that presented in table 4, including detailed occupation and field of degree fixed effects, and excluding the information on usual hours of work.

The results shown in table 7 are in large consistent with the findings elsewhere in the literature. Younger workers are the most likely to work in a better-matched job, but that match quality declines monotonically with age. The oldest workers in the sample work in jobs that have an average index of match quality that is 0.10 standard deviation points below that of the youngest cohort.

The coefficients regarding gender indicate that women are more likely to work in jobs with greater mismatch than men, even though our previous results (table 6) showed that women receive higher wages than men when working in better-matched job. This could be explained because women's reasons to be mismatched tend to be demand-sided, which means that they are more related to family and amenities, reflecting the fact that women's utility functions may not prioritize wages as much as men's do (Robst 2007b).

Regarding marital status and the relationship to the head of the household, they can be seen as aspects that describe the responsibilities of the individual in the household, as well as the flexibility to move in order to search for a better job match. Compared to married individuals, singles work in jobs that are a slightly better matched than married people. To some extent this could be related to the fact that single individuals are more mobile, thus more likely to have a wider range during their job search. Other working-age members in the household, namely "children and other," have a stronger tendency to work in worse job matches. Since they are likely to be dependent on the head of the household's labor choice, they are also more likely to be less mobile, which forces them to adapt to the conditions imposed on them, e.g., smaller labor market or fewer alternatives, resulting in the observed lower quality of job match.

In terms of race, blacks and other—who seemed to obtain a larger payoff from working in a better job match compared to whites—are more likely to work in jobs with a lower match quality compared to whites. It may be that discrimination plays a role, causing these groups to work in occupations that are less related to their fields, even after other individual characteristics are controlled for. As Pager and Pedulla (2015) suggest, discrimination forces minorities like African Americans to use a job search strategy of net widening (greater range of occupation types and occupational characteristics) that will allow them to maximize the probability of finding less-discriminatory job opportunities. However, this strategy may also imply a tradeoff within the education-occupation match quality in order to avoid discrimination in their job environment.

Interestingly, however, is that these patterns are not observed for Hispanics and immigrants. As the results suggest, these two groups seem to work for jobs that are as well matched as whites

and native citizens; however, as will be seen later, this only happens after language barriers are accounted for. In addition, highly educated immigrants are also more likely to have very specialized fields of study, which may be counteracting other market discrimination forces that affect their job choice outcomes.

An initially puzzling result is that coefficients associated with graduate degrees appear to have a negative impact on finding a job that is a good education-occupation match. One should keep in mind, however, the indices of match quality were constructed based on the fields of education related to individuals' bachelor's degree. According to Sax (2001) and Paglin and Rufolo (1990), it is not uncommon that people pursuing a graduate degree choose a field that is not necessarily the same as their original undergraduate field of study (there is no persistence in majors), especially when it comes to specialization degrees. This may explain why one observes that holding a master or a professional degree reduces the likelihood of working in a well-matched job.

The two variables that are closely related to skill level are if individuals indicate they have any disability or difficulty, and an assessment on their own ability to speak English. The results are as expected. As people with some type of disabilities face barriers in the labor market, they may be forced to work in jobs that are more flexible but less related to their fields of study, or pursue fields of study that provide more generalizable skills. Finally, an aspect that is strongly related to working in a poorer job match is the ability to speak English.¹² The estimations suggest that except for people who indicate they speak English "very well," people who speak other languages at home are far more likely to work in a job that is not related to their field.

In addition to the variables explored above, in table 8 we analyze additional aspects related to workers mobility and market restrictions. The first aspect to be considered is household structure. The results here suggest that neither the presence of other adults nor children in the household have any influence on the degree of match of a job. The presence of other employed adults in the household, however, has a statistically significant and negative effect on the

¹² Since the sample is composed of a pool of highly educated workers, less than 1 percent of the sample indicates that they do not speak English well, and only 3 percent indicate to speak English "well."

matching indices. As suggested before, it is possible that once other adults in the household are employed, it increases the restrictions on the job search of a person, increasing the possibility of them working in a less-related job.

The next aspect to consider relates to homeownership. Homeownership status can have ambiguous effects on the job search. On one hand, Valletta (2013) suggests that there is a “house lock effect” to ownership that increases the likelihood of remaining unemployed, as it restricts workers’ search spectrum. Coulson and Fisher (2009), on the other hand, comparing different theory models at the aggregate level found that homeowners are less likely to be unemployed, but their wages are lower than renter’s wages. In a similar way, Brown and Matsa (2016) suggest that in a depressed market, one can expect that owning a house will have a negative impact on the match of a job, forcing workers to apply for nearby jobs. In periods with high unemployment, this may cause workers to seek jobs of lesser match quality. Renters, on the other hand, are more mobile and one would expect them to work in jobs that are a better match.

When controlling for homeownership, homeowners with a mortgage are treated differently from those without a mortgage and renters because, as Havet and Penot (2010) mention, residential stability affects job location and, through this, job match quality. While we expected renters to be more likely to work in jobs with a better match, the results suggest that renters and homeowners with no mortgage work in worse-matched jobs. It is possible that homeowners without a mortgage face the highest pecuniary and nonpecuniary costs of moving to a different location, which may further restrict their job search options and increase the likelihood of working in a less-related job. Brunet and Havet (2009), using data for France, found that homeowners are more likely to feel overeducated, which could be caused by homeowners placing more importance on their housing amenities and family’s stability over properly matched occupations. Havet and Penot (2010) also point out that mobility costs play a main role when homeowners decide not to move for a better job match. We believe this may also be related to the fact that in the United States, public schools are assigned according to residential geographic criteria, which could affect the decision to keep a mismatched job.

A possible explanation for the negative coefficients on renters on match quality could be related to their financial vulnerability. Green (2001) mentions that most of residential rent contracts reset annually, which makes renters face a high risk of price change each year; along the same line, Van Vuuren (2009) found, using data from the Netherlands, that unemployment duration is longer for renters than for homeowners. This financial vulnerability could lead renters to prefer jobs that guarantee financial stability over match quality.

One aspect that may be important to consider when choosing a job may be the restrictions it may impose on workers' other activities. Individuals who attend school may be more willing to work in jobs of a lower-quality match as a trade-off with a more flexible work schedule while preparing to move to a better job match. In our specifications, people who indicate they are currently attending school also work in a job that is, on average, less related to their field of education.

Regarding being veteran, our results show that they are less likely to have a job that matches their education. This could be explained by civilian employers providing differential treatment to veterans and nonveterans while hiring, and also due to veterans' transferability of skills. Kleykapm (2009) found that white veterans with administrative experience (easily transferable skills) compared to civilians with the same skills were treated with little difference by job seekers; however, Black and Hispanic veterans were treated less favorably than their civilian counterparts. About skills that are hard to transfer, when veterans in general (white, black, or Hispanic) with a specialty in combat arms (hard-to-transfer skills) were compared to civilians with administrative experience, veterans were treated far less favorably. This may lead to veterans accepting jobs even though they do not match with their fields of study. On the other hand, Routon (2014) found that military service in the 21st century favors veterans through a higher probability of college enrollment only for minorities and women, and argues that at least for white male veterans, military training may have become a substitute for college education during the few last years. This could be understood as veterans using their military training as education, which does not necessarily match with their occupations.

The last three aspects to consider are related to the expected job market opportunities attached to working in a specific occupation and having a specific field of specialization. Using pooled data for 2011–15, unemployment rates by detailed field of study are estimated to capture field-specific expected job market opportunities. Using the same data, an index of the expected median wage by occupation as a proportion of overall median wages is estimated to capture the role of expected earnings associated with working in a specific occupation. Finally, as a measure of working environment and vertical mismatch, the proportion of workers with at least a bachelor's degree by occupation is also included as control variable. Because these variables vary only across detailed field of education and detailed occupation, the model specifications are modified to include only the aggregated field of education and occupation fixed effects.

The estimations indicate that the field-specific unemployment rate has a very strong relationship with working in a poorer-quality job match. A 1 percentage point increase in the field-specific unemployment rate reduces the index of job match quality by up to 0.15 standard deviation (std) points based on I_{MQ}^1 , and 0.28 std points based on I_{MQ}^2 . This is not unexpected given that standard job search market models suggest that when unemployment is high and the likelihood of finding a good job match is low, people are more willing to work in occupations that are less related to the field of their expertise. Our results are in line with those of Wolbers (2003), who found for school-leavers in Europe that structural characteristics (such as unemployment) increase the likelihood of occupational mismatch, as well as those of Robert (2014), who, using data from graduates in post-communism economies, found that a precarious labor market position (such as unemployment) may increase the odds of vertical and horizontal mismatch.

There is no surprise in these results given structural characteristics' strong influence over workers' decisions about education and occupation. As Altonji, Arcidiacono, and Maurel (2016) mention, the allocation of students across fields of study is affected by business cycles and, when they are in the labor market, the aggregate effects of labor market conditions affect wages through occupational choice.

The impact of expected median wages¹³ has a somewhat ambiguous result. Using the first matching quality index (I_{MQ}^1), the results suggest that there is a trade-off between working in a worse job match and higher expected earnings. However, this result is not observed when using the second matching index (I_{MQ}^2) (column 6). Some examination of these results shows that when using a more parsimonious specification (not shown here), the measure of expected median earnings has a negative coefficient for both indices. It is possible that because the second index has a natural upper-bound truncation on its distribution that there is not enough variation left after controlling for other characteristics to identify the impact of expected earnings on the second match quality index.

Finally, the proportion of workers with at least a college degree has a positive and statistically significant coefficient. This suggests that, after controlling for broad occupation and fields of education categories, working in an occupation with a better vertical match (higher proportion of workers with college degree) also improves the chances of working in an occupation that is a better match for the field of occupation.

¹³ Expected median wage by occupation is estimated to capture the role of expected earnings associated with working in a specific occupation.

Table 8. Exploring the Determinants of the Education-Occupation Match

	Index MQ1			Index MQ2		
	(1)	(2)	(3)	(4)	(5)	(6)
Other adults in the household	0.0024 [0.0072]	0.0036 [0.0073]	0.0045 [0.0075]	0.0008 [0.0064]	0.0055 [0.0068]	0.0071 [0.0072]
Other employed adults	-0.0189* [0.0051]	-0.0201* [0.0052]	-0.0193* [0.0053]	-0.0163* [0.0045]	-0.0200* [0.0048]	-0.0199* [0.0051]
Any children in household	-0.0071^ [0.0041]	-0.0074^ [0.0042]	-0.0046 [0.0043]	-0.0068^ [0.0036]	-0.0063 [0.0039]	-0.0005 [0.0041]
Homeownership						
Owns a house, no mortgage	-0.0158* [0.0051]	-0.0147* [0.0052]	-0.0127+ [0.0053]	-0.0168* [0.0045]	-0.0158* [0.0048]	-0.0139* [0.0050]
Rents	-0.0166* [0.0048]	-0.0176* [0.0048]	-0.0230* [0.0049]	-0.0128* [0.0042]	-0.0153* [0.0045]	-0.0269* [0.0047]
Attends school	-0.0707* [0.0072]	-0.0735* [0.0073]	-0.0977* [0.0075]	-0.0581* [0.0064]	-0.0589* [0.0069]	-0.0718* [0.0073]
Migrated last year	-0.0250* [0.0052]	-0.0249* [0.0053]	-0.0260* [0.0054]	-0.0216* [0.0046]	-0.0258* [0.0050]	-0.0300* [0.0052]
Is a veteran	-0.0714* [0.0088]	-0.0735* [0.0089]	-0.0771* [0.0091]	-0.0569* [0.0079]	-0.0607* [0.0083]	-0.0628* [0.0086]
Unemployment rate in field (2015 5yrs data)		-0.1379* [0.0044]	-0.1482* [0.0044]		-0.2405* [0.0042]	-0.2852* [0.0044]
Occupation median earnings index (2015 5yrs data)			-0.0855* [0.0111]			0.0070 [0.0101]
Proportion of BA+ workers in occupation			0.0074* [0.0002]			0.0077* [0.0002]
State fixed effect	x	x	x	x	x	x
Detailed field of degree fixed effects	x			x		
Detailed occupation fixed effects	x	x		x	x	
Aggregated field of degree fixed effects		x	x		x	x
Aggregated occupation fixed effects			x			x

Note: Standard errors in brackets: ^ $p < 0.1$, + $p < 0.05$, * $p < 0.01$. The specification follows that presented in table 7, except for the use of different levels of detail for the field of degree and occupation fixed effects.

6. CONCLUSIONS

In this paper, we construct two indices that capture the matching quality between fields of education and occupations. These indices are constructed based on the observed distribution of college-educated workers across fields of education and occupation classifications. Under simplifying assumptions, the indices capture the extent to which a better job match is characterized by how large the concentration of workers in a specific field of education-occupation combination is, and the extent to which the observed concentration is different from a random job assignment.

The methodological approach used to analyze the causes and consequences of an education-occupation match has two drawbacks. First, our measures of match quality are data driven; they are not a measure of a true match between the skills acquired along the higher education path and the skills demanded at workers' occupations, but rather a measure that depends on the assumption that the market assigns jobs in the most efficient way. Second, we are not able to control for other aspects that may have driven individuals to choose specific education majors or work in specific occupations. It is possible that aspects of self-selection and endogeneity regarding education and job choice may be affecting the estimated relationships.

However, in spite of these limitations, we believe that our results show some interesting insights. Estimations from the wage equations suggest there is a payoff from working in a job that is a good match with workers' educational background, oscillating around 3 percent for a 1 std point change in the match quality index. This job match premium seems to be larger for older workers, women, ethnic minorities, and immigrants.

The exploratory analysis of determinants of job match quality suggests that the groups that are more likely to have a larger payoff from working in a better-matched job are also more likely to work in a worse education-occupation combination. The results also suggest that skills factors—such as having any disabilities, not having full command of English, and factors that affect job mobility—may be hindering individual opportunities to work in jobs with a better match. Last but not least, the role of expected job opportunities (probability of being unemployed), expected wages, and composition of the occupation labor force structure (share of workers in a given occupation with at least a BA degree) have a significant impact on the likelihood of working for better job matches.

This paper contributes to the literature by introducing two objective match quality indices that can be used with any dataset that contains information regarding occupations and fields of study. Because of the data-driven nature of the indices, they can be adapted to any country or region, and can also help to avoid the bias of self-reported information. From a theoretical perspective, based on our findings, we could infer that the education-occupation match quality affects wages, which reflects variations in productivity that are somehow caused by employers filling positions

with workers with different skills, and workers choosing positions that do not coincide with their education.

In terms of policy implications, we contribute to the discussion about how a proper match would benefit individuals and which demographic groups are more vulnerable to having a mismatched job. Through a better understanding of the education-occupation match effects, individuals could make better decisions about the skills that are required in the labor market, and policymakers could shape the education provided to students. This would benefit not only workers and employers, but also society as a whole by reducing the amount of valuable resources (individual and institutional) that go into an education that will probably not be used.

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