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Job congruence, academic achievement, and earnings ☆

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ABSTRACT

This study combines a widely held view of how earnings are related to education and job tenure (The Mincer model [1]) with the notion that earnings are associated with the quality of an employer–employee job match. The quality of an individual's occupational choice is measured using job congruence, a commonly-used construct in the psychometric literature. Better-matched individuals should be more productive and, as a result, have higher earnings. Previous studies were unable to address the importance of job preferences to earnings because available data do not include both job congruence and individual earnings. The *Alumni Outcomes Survey*, recently produced by ACT Inc., is among the first data sets to include both variables. We use these data to estimate the importance of job congruence on earnings after controlling both for job tenure and for academic achievement, measured by an individual's ACT score. Results indicate that job congruence is positively correlated with earnings, and has effects on earnings that are of almost equal magnitude with years of education.

1. Introduction

The premise of this study is that long term salary attainment is explained partly by academic preparation and partly by matching. While educational status and general academic ability are key predictors of salary attainment, we argue that job congruence—the matching of talents to task—is also important. Both factors are directly related to the career and the educational attainment of students and they have significant policy implications for ensuring earnings potential.

This study combines a widely held view of how earnings are related to education and job tenure with the notion common in psychology, that earnings are also associated with the quality of an individual's job match. Specifically, we use the empirical model presented in Mincer (1974), as discussed extensively in Heckman et al. (2003, 2006a,b) as a benchmark in order to explain variation in earnings. This specification has been widely utilized in the economic literature (Weisbrod and Karpoff, 1968; Ashenfelter and Mooney, 1968; Hansen, Weisbrod and Scanlon, 1970; Paglin and Rufolo, 1990; Blackburn and Neumark, 1992; Grogger and Eide, 1995; Card, 1998). The Mincer model provides a benchmark to isolate the effects of academic achievement, as measured by ACT scores, as well as the effect of job congruence from the effects of increased education. To be clear, we note that what we are measuring is a partial correlation between earnings and job congruence. We do not specify a clear causal model for this effect, although implementing such a structure in a search model would not be difficult. But the correlation between job fit and earnings is of independent interest, and we preferred to stay close in spirit and implementation to the Mincer model.

Closely related to job congruence is the notion of overeducation and educational mismatches. There is an extensive literature which relates overeducation to labor–market outcomes such as earnings (Allen and van der Velden, 2001), job turnover (Topel, 1986; Lentz and Mortensen, 2007; Teulings, 2007), occupational choice (Viscusi, 1979), and job satisfaction (Tsang and Levin, 1985). These papers establish a clear connection between individual earnings and match quality. The congruence measure used in this study provides an alternative measure of match quality which can be introduced to this branch of the literature.

Turning to academic preparation, past research in labor economics examines the Armed Services Vocational Aptitude Battery test (ASVAB), a part of the National Longitudinal Survey of Youth (NLSY), as a measure of general intelligence. This ten scale measure of a range of cognitive

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[1] Following Heckman et al. (2003, 2006), by the term Mincer model we mean the the single equation regression model $\ln[w(s,x)] = \alpha_0 + \rho_s S + \beta_0 x + \beta_1 x^2 + \varepsilon$.

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abilities is associated with salary attainment within the NLSY sample regardless of education level. An alternative approach is to examine academic achievement level, or the degree to which individual students have mastered the range of college and workforce readiness areas. This is the approach ACT has used when constructing its standardized achievement test based on Mathematics, English, Science, and Reading scales. In particular, the ACT is designed to measure the degree to which students have mastered college readiness using a national curriculum survey of high school and college practices. A composite score on the ACT (based on these four subtests) is associated with academic and persistence outcomes (Noble and Sawyer, 2002), and is a commonly held selection variable for college admissions.

Another factor relates to job mobility, and whether individuals stay or change careers. Perez and Sanz (2005) distinguish between job movers and stayers, and between voluntary and involuntary movers.[2] One reason individuals are likely to change jobs relates to what the workforce adjustment literature (Dawis and Lofquist, 1984; Tinsley, 2000) describes as person–environment congruence. Congruence posits that the degree to which an individual's interests, values, and abilities match or are congruent with an occupation's work demands and reward system the greater the degree of satisfaction, tenure, and production. Put another way, an individual worker fulfills work requirements in exchange for financial, social, and psychological rewards. The greater the fit, the greater the likelihood of positive individual and work outcomes. There is a significant psychometric research literature detailing several ways of measuring P–E congruence and demonstrating the relationship between variants of this multidimensional construct and work outcomes (cf. Kristof-Brown et al., 2005), and a smaller literature in labor economics (see, for example, Polachek and Robst, 1998) based primarily on the Knowledge of the World of Work questions contained in the NLSY.

We examine the degree to which individual career interests correspond to the environment of occupational choice. Individual responses to the survey describe the features of the job that they hold as of the survey date. If individuals are unemployed at the time of the survey, they are asked about the last job at which they were employed. Individuals who choose occupations with high congruence to their interests are likely to stay within the broad career represented by initial occupational choice. People staying within a career have higher salary attainment due to natural progression of work opportunity without lost income due to career change. Oleski and Subich (1996) demonstrate, for example, that employed adults in the process of career change move in the direction of higher job congruence. Singh and Greenhaus (2004) argue that people with high congruence are more likely to use rational decision making in occupational choices, and to have greater self and environmental (i.e., work) awareness.

Tracey and Robbins (2006) demonstrate that congruence is related to college outcomes, including cumulative grade point average, retention, and graduation status. They defined congruence as the degree to which individual students' measured career interests corresponded to their college major choice. They use the Euclidean distance between an individual's measured career interests and their occupational choice after placing both data sources on a common coordinate system called the World of Work Map (WWM; ACT, 2001). The WWM is comprised of two underlying dimensions called People/Things and Data/Ideas. These dimensions provide a representation of the six types of career interests found within most models of career interests (cf. Holland, 1997; Tracey and Hopkins, 2001). Given that individual interests and occupational choices can be represented as points on these People/Things and Data/Ideas dimensions, the Euclidean distance between these two points is an indicator of congruence.

One purpose of this study is to study how much standard psychometric measures of achievement (ACT scores) and congruence (*CONG*) explain salary attainment after controlling for the standard Mincer variables, which we describe below. These psychometric factors are not highly correlated with age and years of education, which makes them potentially of great interest. As Tracey, Robbins, and Hofsess (2005) demonstrate, career interest formation and academic achievement (as evidenced by change in ACT score over 8th–10th and 12th grade) are independent processes with both being predictive of college success (Tracey and Robbins, 2006).

We find that both ACT scores and job congruence play both a statistically and a quantitatively significant role in explaining variation in earnings. Higher ACT scores lead to higher earnings, which comes as no surprise in the economic literature where there has been much debate about the independent effects of ability versus educational attainment: the Bill Gates phenomenon (Card, 1998). In addition, better job matches are positively correlated with individual earnings. In terms of order of magnitude, a one unit change in congruence has about the same effect as a one unit change in years of schooling. Further, the effects of ACT scores on earnings are approximately the same magnitude as the effects of job congruence. In addition, we find that the variables used in the Mincer specification follow the same pattern typically observed in the literature. Our results indicate that, for men, 12% of the variation in earnings is attributed to the Mincer variables and approximately 1% of the variation in earnings is attributed to ACT scores and job congruence, separately. Moreover, the Mincer variables are approximately orthogonal to the congruence measure so that the R^2 decomposition is approximately additive.

The rest of the paper is presented as follows. Section 2 describes the basic Mincer earnings function and how it can be interpreted with job congruence measures. Section 3 describes the sample and lists the variables used in this study. A detailed explanation of how job congruence variables are constructed is also provided. Section 4 presents the empirical model and describes the estimation results, and Section 5 concludes.

2. The Mincer model

The Mincer model (1958, 1974) specifies an earnings equation of the form

$$ln[w(S,t)] = \beta_0 + \beta_1 S + \beta_2 t + \beta_3 t^2 + \varepsilon, \tag{1}$$

where S is years of education and t is years of work experience. The coefficient, β_1, is interpreted as the rate of return to schooling, which in this formulation is assumed to be the same for all levels of S. One motivation for this earnings function is the compensating variation model (Mincer, 1958). If individuals are assumed to have identical abilities, perfect certainty about future outcomes, and maximize wealth, then they solve the problem:

$$\max_S V(S) = w(S)\int_S^T e^{-rt}dt = \frac{w(S)}{r}\left(e^{-rS} - e^{-rT}\right) \tag{2}$$

As Heckman et al. (1999) note, an equilibrium in this case requires $V(S) = V(S')$, $\forall S'$. Therefore, equating wealth across different levels of schooling and taking logs yields

$$ln\, w(S) = ln\, w(S') + r * S + ln\left[\left(1 - e^{-rT}\right)/\left(1 - e^{-r(T-S)}\right)\right] \tag{3}$$

The third term in Eq. (3) is an adjustment term for finite age; it goes to zero as T gets large. The implication of Eq. (3) is that the logarithm of earnings should be linear in years of schooling and

[2] There is some disagreement between the psychometric and econometric literatures with respect to job mobility. Perez and Sanz (2005) find that job movers regardless of reason have lower earnings than those who stay in jobs. However, Bowlus and Neumann (in press) show that job tenure accounts for only a modest percentage of the growth of earnings. By contrast, earnings' growth attributed to switching to higher-paying jobs accounts for a much larger percentage of earnings' growth across the earnings profile. Our study regards job congruence as whether individuals are well-matched to their broad career choices, rather than an individual job.

whatever else determines ln $w(S')$. In the standard Mincer approach, ln $w(S')$ is assumed to grow quadratically in age or experience, resulting in the wage equation shown in Eq. (1). If congruence affects earnings capacity, we can rewrite Eq. (2) as

$$\max_S V(S,c) = w(S,c)\int_S^T e^{-rt}dt = \frac{w(S,c)}{r}\left(e^{-rS} - e^{-rT}\right) \tag{4}$$

where c is the measure of congruence. The same arguments that lead to Eq. (3) yield the congruence-modified earnings function

$$ln\, w(S,c) = ln\, w(S,c') + r*S + ln\left[\left(1-e^{-rT}\right)/\left(1-e^{-r(T-S)}\right)\right] \tag{5}$$

This treats c as a permanent characteristic of a worker, which is an hypothesis that could in principle be tested, although not with data currently available. A useful practical specification is to allow the effect of job congruence to vary with education level, as in Eq. (6)

$$\ln w(S,c') = \beta_0 + \beta_1 S + \beta_2 t + \beta_3 t^2 + \beta_4 c + \beta_5 c*S + \varepsilon \tag{6}$$

3. Data and variables of interest

Data from the ACT *Alumni Outcomes Survey* were collected from 93,229 college alumni, with 64% females and 36% males responding. These data are cross-sectional and were collected between 1991 and 2006. Approximately 300 colleges and universities in 42 states across the U.S. were represented. These institutions included both public (63%) and private (37%) colleges and universities, vary in size from small to large, and they offer a range of degrees (e.g. Associate, Bachelor, Doctoral, and/or Professional degrees). Participating institutions self-selected and they determined the alumni population to survey. This sample consists of only individuals who have graduated from either a two- or a four-year degree program. The data do not contain individuals who drop out of college. Over 90% of respondents received surveys via the U.S. mail. Response rates typically ranged from 23 to 28%. These are reasonable rates for survey research conducted with college alumni.

The *Alumni Outcomes Survey* is a service provided by ACT. Its purpose is to assess alumni perceptions regarding the college's impact on their personal and professional growth and development, and to provide a detailed employment and educational history. The *Alumni Outcomes Survey* collects information from college alumni on basic demographics, employment history and experiences (e.g. first job, current job, salary, satisfaction with job benefits, etc.) college major, college grades, educational aspirations, degree attainment, importance of education for developing specific skills, college satisfaction, involvement in activities and organizations, continuing education, etc…

The *Alumni Outcomes Survey* is a unique sample because it is the largest sample, to our knowledge, to match earnings and occupational variables to detailed educational variables. This provides a better way to examine the relationship between these two factors. Further, the data span several years, and can provide a reasonably clear picture of the relationship between the earnings profile and educational attainment. Note that participants of this sample are not re-interviewed, so the data represent a cross-section of observations for each year.

Our sample was drawn from these data. These data were matched to ACT historical records that contained ACT Assessment information, screened for valid social security numbers, and screened for valid ACT test scores. The survey was not conditioned on whether an individual had taken the ACT exam so we expect some reduction in the size of the sample. We focus on the male participants to avoid the well-known problems of part-time employment of women. There were 8488 alumni who had ACT records and valid data. The sample is restricted to the years 1993 to 2005 because there were few observations for 1991 and 1992. Eliminating missing observations and imposing these restrictions on the survey years result in a sample with 4647 men. Further, some observations are missing the necessary survey items to compute their congruence scores. These individuals are also excluded from the sample. The final sample consists of 3821 observations.

Table 1
Earnings variable frequencies.

Annual Earnings	Freq
$14,999 or less	8.79%
$15,000–$19,999	6.36%
$20,000–$24,999	11.41%
$25,000–$29,999	14.34%
$30,000–$39,999	27.35%
$40,000–$49,999	15.86%
$50,000–$59,999	8.61%
$60,000–$69,999	3.32%
$70,000 or more	3.95%

3.1. Earnings

The earnings variable in the survey is an ordered categorical variable, with nine different categories. If the earnings variable was measured continuously the semiparametric estimator of choice would be OLS, but this is not the case here. One method of treating earnings in this case is to use the midpoint of each interval as the measure of earnings, an approach that we shall follow with a few additional checks. The problem with the midpoint imputation method is that it can lead to inconsistent estimates of the regression parameters (Stewart, 1983). This problem can be avoided by using an interval estimator coupled with a distributional assumption about the error term. In the important special case where the interval cut points are known, which is the case here, both the parameters β, and the scale parameter σ are separately identified. Identification is the result of the distributional assumption. Specifically, if we denote the interval endpoints as y_j, $j=1,\ldots,9$, the probability of observing an observation in the interval $<y_j, y_{j-1}>$ is $F(y_j|x) - F(y_{j-1}|x)$. If F is assumed to be a Gaussian distribution with parameter $\Theta = (\mu,\sigma)$, then it is possible to identify $\mu = x\beta$ and σ when the cut points are known. The assumption of a Gaussian error distribution can be checked by estimating an ordered probit model (without specifying the cut points) and directly comparing the log likelihood of the interval estimator with that of the ordered probit.[3] To conduct the analysis, we assign the value of the midpoint of each earnings range, except for the open-ended range of >$70,000. Values in the "$70,000 or more" category are assigned a value of $139,144.90,which corresponds to the conditional median earnings of college educated males, conditional on earning more than $70,000. These values are taken from the March 2005 Current Population Survey (CPS), and all values of earnings are transformed to be in terms of 2005 dollars. Table 1 provides the frequencies of each category.

3.2. Age and age^2

The survey asked the birth year of each participant. Age is calculated by subtracting the individual's birth year from the year the survey was administered.

3.3. Years of education

Years of education are computed using the highest degree completed by an individual. This variable takes a value of 13 if the individual obtained a degree from a vocational school. Individuals with associate's degrees are assigned a value of 14. A bachelor's degree is assigned a value of 16, a master's degree is assigned a value of 17, any

[3] There are other tests that can be used to test the distributional assumption — see Mora and Moro-Egido (2008) and Horowitz and Spokoiny (2001).

other six-year degree is assigned a value of 18, and doctoral degrees (both Ph.Ds and M.D.s) are assigned a value of 21.

3.4. ACT composite score

The ACT is comprised of Mathematics, Science, English and reading tests. Each test is constructed to represent the curriculum and skills necessary to be successful in postsecondary education. Each is a multiple choice, timed test with strong reliability and validity support (ACT, 1997). Test lengths vary with question pools ranging from 40 to 75 questions. An overall composite score, ranging from 1 to 36, is calculated as the average of the four subtest scores.

3.5. Occupational choice congruence

Individual measured interests are obtained using the Unisex edition of the ACT interest inventory (UNIACT; ACT, 1995). The UNIACT consists of 90 activities to which respondents can choose alike, indifferent, or dislike response. Responses yield six RIASEC scores: Realistic, Investigative, Artistic, Social, Enterprising, and Conventional. There is extensive psychometric support for this widely used instrument (ACT, 1995). Two dimensional interest scores were calculated using geometric weighting of RIASEC scales to locate Things/People and Data/Idea coordinates. The structure of the UNIACT RIASEC scales, and underlying Data–Things, People–Ideas coordinates, also is supported (Day and Rounds, 1998; Prediger, 1982, Prediger and Vansickle, 1992; Rounds and Tracey, 1993).

Two indices of congruence are available, both measured as the Euclidean distance between the point in two dimensional spaces represented by an individual's career interests and the point represented by the individual's occupational choice. The first index is based on the occupational choice indicated by the individual upon completion of college, and the second is computed using the observed occupation in which the individual is employed at the time of the survey. These measures are highly correlated ($\rho = .34$), so we focus on the congruence measure based on the job at the time of the survey. We use ACT's (1995, 2001) World of Work (WWM) Map to locate these points before calculating the Euclidean distance. The original WWM map is derived from Holland's (1997) RIASEC typology of career interests which can be represented as a point in two-dimensional space of People–Things and Data–Ideas (Prediger, 1982; Prediger and Vansickle, 1992). This representation is supported in the literature (Rounds and Tracey, 1993; Tracey, 2002), and reflects the belief that career interests have specific structural characteristics located within circular space.

Using the WWM map, we classify the location of 1100 distinct occupations into 23 career areas by using basic work tasks (ACT, 1995, 2001). The basic work tasks were derived using the U.S. Department of Labor's Occupational Information Network (O*NET) and Dictionary of Occupational Titles databases; these basic work tasks were rated on the Data, Ideas, People, and Things dimensions. On the basis of these scores, occupations were grouped into career areas and plotted on the

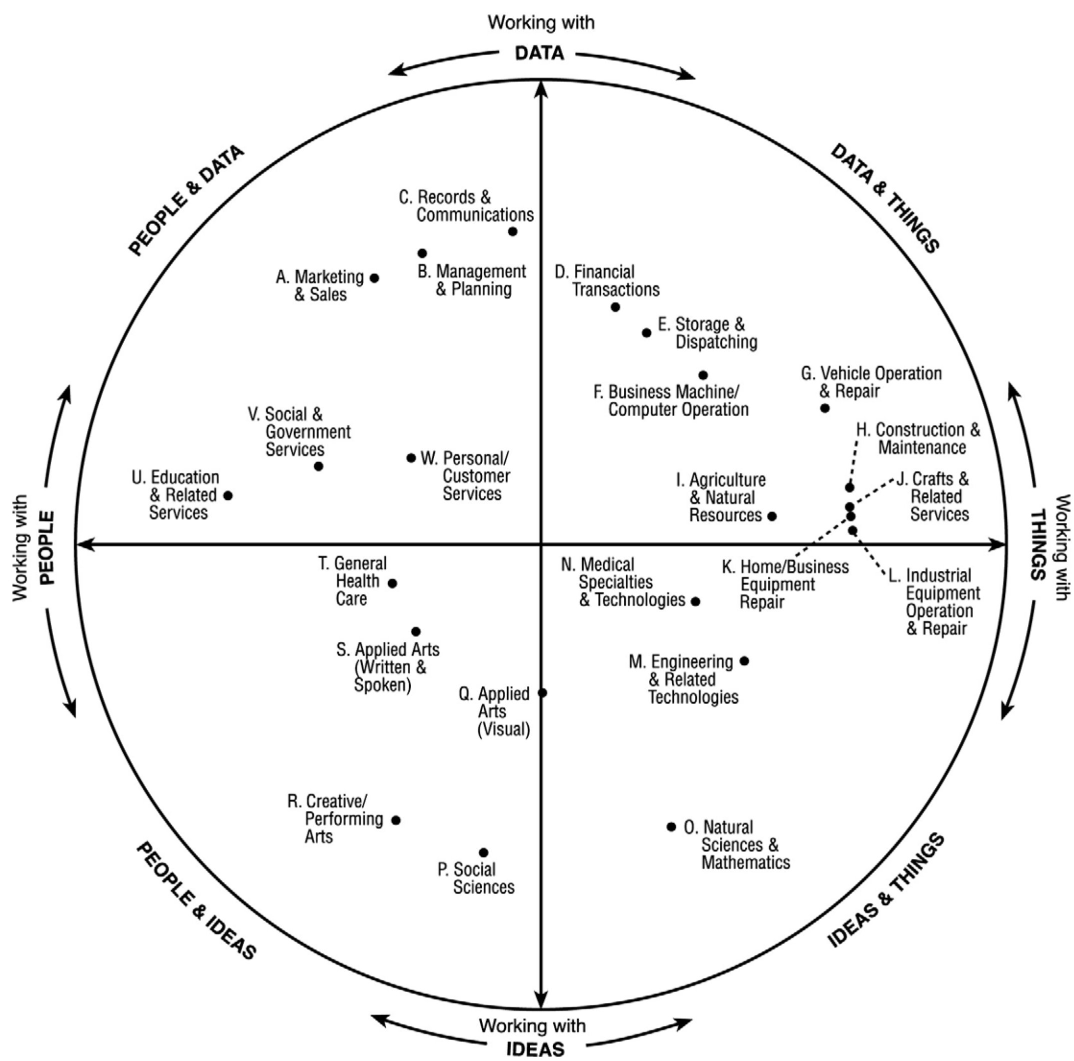

Fig. 1. The World of Work Map.

WWM. The nature, content, and number of career areas were repeatedly refined to cover the large majority of occupations. Prediger and Swaney (2004) provide a complete history and description.

At the time of ACT test-taking, students are asked to choose from a list of the 23 career areas. They are: A. Marketing and sales, B. Management and planning, C. Records and communications, D. Financial transactions, E. Storage and dispatching, F. Business machine/computer operation, G. Vehicle operation and repair, H. Construction and maintenance, I. Agriculture and natural resources, J. Crafts and related services, K. Home/business equipment repair, L. Industrial equipment operation and repair, M. Engineering and other applied technologies, N. Medical specialties and Technologies, O. Natural sciences and mathematics, P. Social sciences, Q. Applied arts (visual), R. Creative/performing arts, S. Applied arts (written and spoken), T. General health care, U. Education and related services, V. Social and government services, and W. Personal/customer services. These 23 career areas are placed on a circular map defined by the dimensions of Things/People and Data/Ideas with Cartesian coordinates. All career areas were translated using explicit algorithms into positions on a circular Things/People and Data/Ideas map with scores commensurate with those of standardized interest scores. Fig. 1 displays the WWM and the locations of the occupational choices.

The distance between the individuals' scores and the WWM point was calculated using the dimensional scores of each. Specifically the job congruence variable is given by:

$$\text{job congruence} = \left([\text{interest}(T/P) - \text{WWM}(T/P)]^2 + [\text{interest}(D/I) - \text{WWM}(D/I)]^2\right)^{1/2} \tag{7}$$

where T/P denotes the coordinates along the Things-People axis, and D/I denotes the coordinates along the Data-Ideas axis. High Euclidean distance scores indicated low congruence between interest and occupation choice; low Euclidean distance scores represented high congruence. A Euclidean distance score of zero indicates perfect congruence. The Euclidean distance index of congruence was used by Tracey et al. (2005) in their examination of interest-career goal congruence. Although this usage is common in the psychometric literature, it is a bit jarring to economists because the index is actually a measure of lack of congruence, i.e., higher values indicate a worse match. In the comparisons we make below, we always refer to increases in job congruence as decreases in this index. It is of some interest to note the correlation structure of these variables. ACT is strongly correlated with years of education ($\rho_{EDUC,\,ACT} = 0.23$; p-value<0.001), while congruence is not ($\rho_{EDUC,CONG} = -0.01$; p-value<0.24).

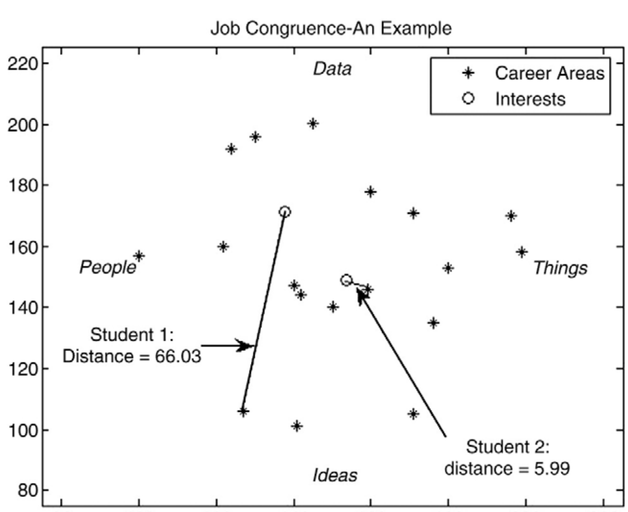

Fig. 2. Job Congruence: An Example.

Table 2
Descriptive statistics.

Variable	Mean	Std. Dev.	Min	Max	Obs
Log(salary)	10.47	0.59	8.92	11.84	3821
Education	16.05	1.06	13.00	21.00	3821
Frequencies	25.83	2.07	18.00	54.00	3821
	Vocational			1.33%	
	Associates			6.86%	
	Bachelors			79.01%	
	Masters			10.02%	
	Six Year			0.29%	
	Ph.D.			2.49%	
Age	25.83	2.07	18.00	54.00	3821
$\text{Age}^2/100$	6.71	1.17	3.24	29.16	3821
ACT score	22.81	4.15	11.00	34.00	3821
Cong: job	36.51	16.54	0.88	92.54	3821
Cong: job × education	584.56	266.35	14.00	1490.99	3821

To highlight the measurement of congruence we provide an example in Fig. 2. In the figure, People and Things are plotted on the horizontal axis and Data and Ideas are plotted on the vertical axis. Common scales are created with an origin point of 150. Both career areas and individual interest scores are transformed using this common scale. The asterisks highlight the fixed placement of each of 18 career areas most likely to crosswalk to an occupational choice of someone entering post secondary institutions. Each star corresponds to the A through W list provided earlier. We highlight two individual respondents. Student 1 picked career area R, Creative/Performing Arts, as first occupational choice. Their measured career interest, depicted with a circle is also provided. One can see that the Euclidean distance is equal to 66.03, which is relatively large. This means that the fit or congruence between occupational choice and interest is poor. Alternatively, Student 2 chose career area N, medical specialties and technologies. The distance to their measure career interests is small, resulting in a high degree of fit (job congruence = 5.99). As can be seen, Student 1 is planning on a career in the creative/performing arts, but his interests appear to fit more with "Data" rather than "Ideas." Student 2 is planning on a career in medical specialties and technologies and her interests are well-aligned with those plans.

4. Results

To examine the effects of the different variables on earnings, we present ordinary least squares (OLS) regressions using *log* salary as the dependent variable. The independent variables for the regressions include: the number of years of schooling (education), the age of the individual (age), age^2 (age^2), ACT score, and job congruence (cong:). Descriptive statistics of each variable are provided in Table 2.

Table 3
OLS regressions for men.

	(1)	(2)	(3)	(4)
Education	0.0782	0.0678	0.0647	0.0345
	(0.009)	(0.009)	(0.009)	(0.017)
Age	0.2823	0.2804	0.2786	0.2763
	(0.029)	(0.029)	(0.029)	(0.029)
$\text{Age}^2/100$	−0.3812	−0.374	−0.371	−0.3688
	(0.052)	(0.052)	(0.052)	(0.052)
ACT score		0.01	0.0093	0.0093
		(0.002)	(0.002)	(0.002)
Cong: job			−0.003	−0.0201
			(0.001)	(0.008)
Cong: job × yearedu				0.0011
				(0.001)
Constant	4.4811	4.4221	4.6232	5.1555
	(0.413)	(0.412)	(0.412)	(0.481)
N	3821	3821	3821	3821
R-squared	0.12	0.12	0.13	0.13

The above regressions use the log of salary as the dependent variable. Standard errors are provided below each coefficient estimate in parentheses.

Regressions are estimated for men to examine the effects of academic achievement and job congruence on earnings. Table 3 provides OLS estimates for men.[4]

Column (1) of the table provides the coefficient estimates of the standard Mincer (1974) regression. The Mincer regression provides a benchmark against which we compare the effect of including both ACT scores and job congruence. These benchmark results are consistent with results commonly observed using this model. The coefficient on years of education is positive and statistically significant, and the return on an additional year of education is approximately 8%.[5] Both of the coefficients on the age variables are significant, and have the expected sign. Earnings are a concave function of age, reaching a maximum at age 38.

When ACT score, which is frequently interpreted as a measure of ability (Card, 1998) is added to the Mincer specification, the coefficients on years of education, age, and age squared do not change in either sign or significance, and their magnitude remains approximately the same. The coefficient on ACT score is positive and statistically significant, suggesting that ability as well as years of education plays a role in describing the variation in earnings. A 10% increase in ACT score corresponds to a 2.2% increase in salary, according to column (2) of Table 3. A positive relationship between academic achievement and earnings is a common finding in the economic literature (Weisbrod and Karpoff, 1968; Ashenfelter and Mooney, 1968; Hansen, Weisbrod and Scanlon, 1970; Paglin and Rufolo, 1990; Blackburn and Neumark, 1992; Grogger and Eide, 1995), so it is not surprising that this positive relationship exists here.

Consider the effects of education and job congruence in columns (1)–(4) of the table. Column (1) contains the results of including the traditional Mincer variables. In this case the marginal return to an additional year of education is about 7.8%, which is slightly lower than other estimates for the 1990–2000 period but not especially so. To make comparisons about magnitudes of effect across variables we consider the impact of a one-standard deviation change in the relevant variable. Thus, in column (1) a one standard deviation change in years of education produces, using the standard deviation reported in Table 2, an 8.3% increase in annual earnings. Adjusting for ACT score, as in column (2), changes this slightly, reducing the one standard deviation change to 7.2%.[6] Column (3) of the table includes the effect of job congruence—the matching of individual interests with job characteristics. A one standard deviation increase in years of education produces a 6.9% increase in earnings; a one standard deviation decrease in job congruence results in a 5.0% increase. In other words, the effects of increasing years of education and increasing job congruence are of the same order of magnitude, in this case congruence effects are 72% of the education effect.

Finally, in column (4) of the table we report the effects of allowing the effect of job congruence to vary with the level of education. The marginal returns are given by

$$\frac{\partial \ln y}{\partial education} = \beta_1 + \beta_5 * c, \text{ and} \tag{8}$$

$$\frac{\partial \ln y}{\partial c} = \beta_4 + \beta_5 * Education \tag{9}$$

Table 4
Comparison of full-model estimates.

	(1) OLS	(2) INTREG	(3) OPROBIT	(4) OPROBIT*SIGMA
Education	0.0345	0.0451	0.0682	0.0354
	(0.017)	(0.016)	(0.032)	
Age	0.2763	0.3014	0.5923	0.3076
	(0.029)	(0.028)	(0.055)	
$Age^2/100$	−0.3688	−0.3974	−0.7763	−0.4031
	(0.052)	(0.049)	(0.096)	
ACT score	0.0093	0.01	0.0259	0.0134
	(0.002)	(0.002)	(0.004)	
Cong: job	−0.0201	−0.0163	−0.037	−0.0192
	(0.008)	(0.008)	(0.015)	
Cong: job × yearedu	0.0011	0.0008	0.0019	0.001
	(0.001)	(0.001)	(0.001)	
Constant	5.1555	4.5373		
	(0.481)	(0.466)		
σ	0.5506	0.5193		
$-\log L$		−7946.4	−7341.9	

A comparison of the model in column (4) of Table 3 is provided here. Standard errors are given in parentheses.

We evaluate these changes at the mean values of job congruence and years of education reported in Table 2. Interestingly, the marginal return to education is decreasing in job congruence[7], while the effect of greater job congruence is increased by greater years of schooling. Evaluating these effects at the sample means results in an increase in earnings of 7.9% due to a one standard deviation increase in years of education, and a 4.0% increase due to a one standard deviation change in job congruence.

Job congruence, by itself, explains 1% of the variation in earnings. These results suggest that job congruence explains some of the variation in earnings captured neither by the standard Mincer variables nor by ACT scores. The increase in R-square values between columns (1) and (5) is approximately equal to the explanatory power of the regression of log salary on job congruence, with or without the ability measure, *ACT*. This pattern suggests that congruence or matching is approximately orthogonal to age and education.

Table 4 contains estimates of the parameters of the full model shown in column (4) of Table 3, obtained using OLS (column (1)), interval estimation assuming that log earnings are normally distributed with known cut points (column (2)), and ordered probit with no assumption about the location of the cut points (column (3))[8]. Two features stand out in the table. First, the OLS coefficients and the interval coefficients are very close, except possibly for the constant term. The scale parameter is not identified in the ordered probit results, but if we multiply the ordered probit coefficients by the interval estimates' scale parameter (0.5193) we obtain the estimates shown in column (4) of Table 4. And, again, these estimates are very close to the OLS estimates. We conclude that there is no indication that the OLS estimates misstate any of the effects shown in these data. The second feature of the table that stands out is that the assumption of log normality of earnings is not supported. The chi-square statistic, $-2 \cdot \nabla \ln L$, is about 1200, and the hypothesis of log normality would be rejected at any reasonable significance level.

5. Conclusion

These results highlight the role that job matching has in explaining variability in earnings. We find that job congruence affects earnings to approximately the same order of magnitude that additional years of schooling does. Specifically, we find that a one standard deviation change in job congruence has an effect on earnings that is 51%–72% of a similar one standard deviation change in years of education. Clearly individuals who select jobs consistent with their interests have

[4] Recall that the measure of earnings used in the OLS regressions was computed using an ordered categorical variable and that each value of the salary variable is the midpoint of a range of values. Since individuals in the highest earning category were assumed to have earnings of $139,144.90, the OLS regression coefficients may be affected both by the use of midpoints and by the choice of the top value. To examine the importance of this scaling effect, ordered probit regressions are estimated, using the categories of earnings as the dependent variable instead of the log of earnings. These are summarized below and reported in Table 4.

[5] The rate of return on education from our sample is slightly lower than the estimated rate from the March 2000 CPS, which reports a rate of return of approximately 11%. This may reflect a geographic bias—i,e., the ACT is less frequently taken in the Eastern states of the U. S.

[6] See Griliches (1977), and Card (1998) for similar results about the effect of adding measures of ability on the return to education.

[7] Recall that increases in the measure we have actually means decreases in the congruence between individual interests and occupation characteristics.

[8] The estimates were obtained using Stata's **intreg** and **oprobit** commands.

greater salary attainment. Further research is needed to test the implied causal linkages between worker fit and academic preparation, trajectory of job success, and salary attainment.

One potential extension of our approach relates to the job matching literature. Recent papers in the search and matching literature highlight overeducation, which examines the effects of skilled individuals working in occupations that require only a skill level (Albrecht and Vroman, 2002). Instead of focusing on skill mismatches, it may be useful to examine the effects of mismatches based on measures of job congruence, and to examine both the resulting welfare effects and the difference in earnings between poorly-matched and well-matched individuals. The data used in this study is well-equipped to describe this phenomenon.

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