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Abstract

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KEYWORDS: low-skill jobs

WAGE DIFFERENTIALS, SKILLS, AND INSTITUTIONS IN LOW-SKILL JOBS

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The typical study of wage differentials examines workers at all educational levels and attends closely to the link between education and wages. Little research has looked at determinants of wage differentials specifically among workers with low educational attainment. This study, using the 1998–2002 Bay Area Longitudinal Surveys and the 2001–2003 Occupational Information Network, examines which skills and labor market institutions affected wages in jobs for individuals with a high school education or less and little work experience. The author finds that jobs demanding office/clerical skills, mechanical skills, or the "new basic" skills of reading, math, problem-solving, and communication paid higher wages, on average, than did other low-skill jobs, especially those in which physical skills were relatively important. Also positively associated with wages for these low-skilled workers were union representation and location in an industry containing relatively few low-skill jobs.

In 2001, about 27.5 million Americans, or 23.9% of the labor force, earned less than $8.70 per hour (Mishel, Bernstein, and Bushey 2003). Working full-time, full-year at this wage yields an annual income of $17,400, well below the national median of $33,500. While most individuals who do not continue their education beyond high school are low-wage workers (Appelbaum, Bernhardt, and Murnane 2003), some receive relatively high wages (Holzer 1996), raising the question of which factors give workers with low levels of education a wage that might lead to a middle-class lifestyle and which factors might keep them at poverty-level wages.

Both workers with low levels of education and policymakers committed to increasing wages of such workers have an interest in the answer to this question. If some skills increase wages in jobs for workers with little education and some do not, policymakers might focus policies and programs on building the skills that increase wages. Alternatively, if unionization, but not firm size (for example), increases wages in jobs for individuals with a high school education or less, policymakers might refrain from promoting firm size as a job search criterion for low-skilled workers and instead focus on building or supporting labor market institutions that increase wage floors under unionization.

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A data appendix with additional results, and copies of the computer programs used to generate the results presented in the paper, are available from the author until June 2010 at Human Investment Research and Education Center, California State University, East Bay, 25800 Carlos Bee Blvd., Hayward, CA 94542; nan.maxwell@csueastbay.edu.

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This study examines which skills and institutions increase wages in jobs for workers with a high school education or less. One unusual feature of the analysis is its linking of local job-level data (the Bay Area Longitudinal Surveys, or BALS) with national-level data (the Occupational Information Network, O*NET), an approach that yields some potentially useful methodological insights.

Framework

The plight of workers with no more than a high school education is well documented. Competition from foreign markets (Revenga 1992) and skill-biased technology change have made today's jobs increasingly complex, focusing them on the nonroutine, analytic, and cognitive and moving them away from the routine and manual (Spitz-Oener 2006; Autor, Levy, and Murnane 2003; Autor, Katz, and Krueger 1998). As a consequence, the demand for less-skilled labor has decreased (Berman, Bound, and Machin 1998; Berman, Bound, and Griliches 1994; Krueger 1993) and the jobs held by low-wage workers have transformed to require the "new basic" skills of reading, math, problem-solving, and communication (Holzer 1996; Murnane and Levy 1996). Even production and clerical jobs, traditional sources of employment for low-skilled workers, have upskilled (Cappelli 1993). Individuals with a high school education or less now face a labor market in which new basic skills are increasingly tied to wages (Murnane, Willett, and Levy 1995) and physical and mechanical skills are often used in conjunction with the new basic skills (for example, Bartel, Ichniowski, and Shaw 2003).

Changes in labor market institutions have also changed the nature of low-skilled workers' jobs and the factors influencing their wages (Card and DiNardo 2002). Skill-biased technology change altered workplace organization and the types of goods and services produced (Bresnahan, Brynjolfsson, and Hitt 2002), as well as labor market institutions such as unionization (DiNardo, Fortin, and Lemieux 1996) and the organizational structure of industry (Juhn 1999). Union strength, labor demand, minimum wages, and industry mix all significantly influence metropolitan-area wages for workers with a high school education or less (Easton 2006),[1] and fixed effects exist in firms' determination of wages, suggesting that some firms simply pay higher wages than others (Holzer, Lane, and Vilhuber 2004). Most notably, large firms, firms with lower turnover, and firms in the manufacturing sector pay higher wages to low-wage workers than do other firms, *ceteris paribus.* Finally, unions increase workers' wages even in industries employing large numbers of low-skilled workers (Belman and Voos 2004).

Thus, a fair amount of research supports the idea that both skills and certain dimensions of labor market institutions affect wage differentials between individuals with different levels of education. Less research has examined which specific skills and institutional features (firm size, union status, industry) influence wage differentials *in jobs for low-skilled workers,* perhaps because the empirical nature of the question requires a unique database. To this end, the present research looks at jobs for individuals with no more than a high school education and one year of work experience to identify the types of skills and labor market institutions that determine wages in jobs held by individuals with low levels of education. Although my analysis is grounded in information on wages, skills, and labor market institutions from a single labor market in the San Francisco Bay Area, it also draws from a national database containing detailed information on skills. My analysis of skill requirements, labor market institutions, and wages in low-skill jobs is aimed at establishing the influence of specific skills and institutions on wages in jobs that are held by low-skilled workers. Knowledge of these lines of influence could inform training- and institution-related policies designed to help ensure that workers who possess no more

[1]DiNardo, Fortin, and Lemieux (1996) showed, in addition, that the decline in the real value of the minimum wage also increases wage inequality, especially for women. Because the data in this study do not allow me to evaluate the influence of the minimum wage on wages in low-skill jobs, I implicitly downplay its potential.

than a high school education have a shot at jobs offering wages that might provide for a middle-class lifestyle.

Research Methods

My research design has at least four advantages over that of previous studies. First, for purposes of determining how firms set wages in low-skill jobs, the case study data I use are unusually rich, containing information on wages, skill requirements, union coverage, and characteristics of the firm (size and industry) for jobs available to workers possessing no more than a high school education and one year of work experience. Second, by confining the analysis to one local labor market, I control for many factors that affect the demand for workers with little education, allowing the study to focus closely on skill and institutional determinants of wages in low-skill jobs. Factors that might affect wages or capital substitution for low-skilled workers—labor demand and labor laws such as those mandating a minimum wage[2] or setting workers' compensation parameters, for example—are all held constant in a local labor market.

Third, augmenting local labor market data with national data on skills permits an examination of how results might change using different measures of skills. Such an analysis is important because collecting data on skills is time-consuming and expensive, but often highly desirable. Because many databases contain information on wages but not skills, researchers frequently develop skill measures from national databases for use in analysis (for example, Ingram and Neumann 2006; Autor, Levy, and Murnane 2003). The present research provides an opportunity to test the viability of such measures by comparing estimates using skills constructed from task requirements of the job under analysis with skills constructed from aggregate information about their average use in a specific occupation.

Finally, the two databases used in this study provide a rich array of skill measures. Many previous studies of skills in low-wage positions have focused on the new basic skills (Murnane and Levy 1996; Holzer 1996; O'Neil and Allred 1996). Because my case study database contains skill measures heavily grounded in the "new basics" and the national database contains a plethora of physical and mechanical skill measures, this study takes a broad perspective as to what constitutes skills.

Data

My case study data are taken from the Bay Area Longitudinal Surveys (BALS) (www.hire.csueastbay.edu/Hire/bals.htm). The BALS data come from 405 surveys administered on-site to firms in three San Francisco Bay Area counties from June 1998 to October 2002. Only firms that were hiring in a low-skill job—defined as one requiring no more than a high school education and no more than one year of work experience—were included in the sampling frame.[3] In addition to obtaining general information about the firm, the BALS selected one low-skill position[4] and asked questions about the job (for example, average wage at entry, union representation) and about whether workers in the position were required to perform certain skill-based

[2]Easton (2006) found that both labor demand and minimum wage legislation affected metropolitan-area wage levels for high school–educated workers.

[3]The BALS was fielded in San Francisco, Alameda, and San Joaquin counties with a 21.4% response rate. Firms not currently hiring low-skilled workers or hiring low-skilled workers only through a third party such as a union, temporary help agency, or church were not included in the sampling frame. While temporary help jobs were included in the study through their reporting by temporary help firms, our exclusion of hiring through a third party may cause our results to understate unions' influence on wages, for their influence may be strongest in jobs filled through a union hiring hall. A description of the survey methods, including a comparison of firms in the BALS data set with those in the three-county area, is available at http://www.hire.csueastbay.edu/hire/discpap/abstracts/D04-06-04.pdf. This report shows that construction jobs are less well represented in the jobs sampled for the present study than they are in jobs throughout the three-county area, consistent with the BALS restriction that jobs be available through an open application process.

[4]Firms hiring for only one low-skill position were asked questions about that position. In firms hiring for more than one position, a position was selected for surveying that maximized the variability of jobs in the sample.

tasks.[5] Skills were grouped into six areas: reading and writing, math, communication, problem-solving, use of equipment, and use of computer software. The skill-based tasks and groupings chosen for inclusion in the study were all identified by employers in focus group discussions as those found in low-skill positions.

I augment analysis of the BALS data with analysis of the U.S. Department of Labor's Occupational Information Network (O*NET) 5.1 database (www.onetcenter.org), which provides a detailed assessment of knowledge, skills, and abilities[6]—all called *skills* here for ease in exposition—needed in 974 jobs throughout the country. Full-scale data collection began in June 2001,[7] with additional data gathered yearly on approximately 200 occupations so as to replenish the database every five years. A two-stage design first identifies a statistically random sample of businesses expected to employ workers in the targeted occupations and then randomly samples workers in targeted occupations. One advantage of the O*NET data is that they make it possible to compare the average use of a skill in jobs throughout the nation with its use in jobs for low-skilled workers, defined as O*NET's 135 job zone 1 jobs.[8] My study examines 76 O*NET skills that were used in 20% or more of job zone 1 jobs (the same criterion employed in selecting BALS skills for examination) and uses the SOC-O*NET occupational codes to link them to the BALS data.

Several key differences between the BALS and O*NET measures of skills enable me to explore whether and in what ways the results might vary with different skill measures. First, the BALS measures reflect skills used in tasks in the job under analysis, whereas the O*NET's measures reflect average skills used across groupings of similar jobs—specifically, jobs within the same occupation—throughout the country. Second, the BALS measures were conceived with the purpose of eliciting information about skills used in jobs available to workers with no more than a high school education and one year of work experience, whereas the O*NET measures were designed to elicit information about skills used in a wide array of jobs. The BALS skills therefore measure narrowly defined tasks common to many low-skill jobs (for example, reading memos, reading instructions, reading manuals, reading labels) while the O*NET skills measure a wide range of broadly defined skills (for example, reading comprehension). Third, the BALS skills measure whether skills are required by a job (1 = job requires skills and 0 = not), while the O*NET skills measure the intensity of their use (1 = lowest to 7 = highest).

Empirical Methods

Both the BALS and the O*NET contain a wealth of skill measures. In fact, if all measures were used as covariates, their large number would greatly reduce the degrees of freedom and, most probably, create multicollinearity in multivariate estimations. I therefore employ a factor analysis on skill measures in each database to define a more manageable number of skill measures for use in analysis. Factor analysis assumes the existence of a system of underlying constructs in the detailed measures of skills and uses their correlation to uncover underlying patterns, called factors.[9] Because the factor score computed

[5]The BALS skills used in this study were those respondents were asked about in all three counties (to maximize sample size) and those used in at least 20% of the jobs (to prevent outliers from driving the analysis).

[6]The O*NET defines *knowledges* as organized sets of principles and facts that apply to a wide range of situations; *skills* as developed capacities that facilitate learning and the performance of activities that occur across jobs; and *abilities* as enduring attributes of an individual that influence performance. Data are based on several hundred rating scales in questionnaires completed by sampled workers and one questionnaire completed by occupational analysts using updated information from incumbent workers.

[7]Although the BALS was initiated in 1998, which was prior to O*NET's initial fielding, both surveys were in the field in 2001–2002, with 81% of the BALS completed during that period. O*NET 5.1 was released in October 2003, and BALS data collection ended in 2002.

[8]Job zone 1 jobs "may require a high school diploma or GED certificate," "no previous work-related skill, knowledge, or experience," and "anywhere from a few days to a few months of training."

[9]Because I had no *a priori* expectation of the number of underlying constructs in any of the original skill

from the factor analysis quantifies, in relative terms, the importance of each skill in the factor-analysis–determined skill measure, I use it to measure how much a particular job requires the skills contained in a skill measure.[10] A relatively high and positive factor score indicates that the job requires many of the detailed skills contained in the skill measure. A relatively large negative score indicates that the job requires skills that are generally not part of the skill measure. The factor analysis of the BALS data generated 11 measures of skills, which I call office, writing, sales, problem-solving, arithmetic, report generation, reading forms, reading instructions, measurement, decision-making, and working with others. The factor analysis of O*NET data on job zone 1 jobs generated 10 measures of skills, which I call large motor, mechanical, clerical, small motor, reaction & response, science knowledge, chemistry knowledge, production, flexibility of closure, and public safety & security. The Appendix provides an expanded definition of each skill measure.

My descriptive analysis highlights the skills needed in jobs for workers with low levels of education by comparing skill requirements and wages across occupations and by examining correlations between factor-analysis-determined skill measures to detect patterns in skill use in low-skill jobs. The multivariate analysis examines how wages in the job are related to skills and institutions using the ordinary least squares (OLS) estimation

$$(1) \qquad \mathrm{Ln}\, W_j = \gamma_0 + S_j\alpha_s + \alpha_1 U_j + F_j\alpha_f + \varepsilon_j,$$

where Ln W = the log of the hourly rate of pay in a job (j) for workers with no more than a high school education and one year of work experience; S = a vector of skill measures used in the job; U = a 0, 1 binary variable with 1 indicating that a union represents the worker in the job; F = a vector of variables describing the firm in which the job occurs, including firm size and industrial sector; and ε = the error term.

I use the coefficients' statistical significance ($p \leq .05$) and sign (α) to assess the relationship between a particular skill or institution and wages in the job. The statistical significance provides evidence on whether a specific skill or institution influences wages, while the sign tells us whether the wage effect of that skill or institution is positive or negative. Although human capital theory predicts that skills are associated with higher wages in individual estimations, this relationship might not follow when the unit of analysis is the job and the skills are measured as a function of task requirements in the job. Because some of what we call skills do not require investments (for example, physical abilities), firms would not necessarily increase wages for their procurement unless they were relatively scarce.

I estimate equation (1) under different specifications to determine the sensitivity of the results. The first model establishes baseline results by estimating a fully specified equation (1) using both the BALS and the O*NET skill measures. The second set of estimations uses only one set of skills, either the BALS or the O*NET measures. Comparing the size and significance of α's between the estimates using all skill measures and those using only one set of measures permits an assessment of whether the results are sensitive to the measures included in the estimation. Further, comparing the R^2 between the estimations using only the BALS skill measures and those using only the O*NET skill measures allows us to assess whether wage variation can be explained as well by using information from a national database as by using skill measures developed from tasks performed in the jobs under analysis.

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measures, I allowed the factor analysis to determine the number of factors accounting for the observed covariation in each construct. I specified an oblique factor solution, which produces correlated extracted factors, since it seemed reasonable to assume correlation between the skills. I identified only factors with eigenvalues exceeding one. The factor analysis of the BALS data explained 62.2% of the variance in skills required in BALS jobs, and the factor analysis of the O*NET data explained 88.7% of the variance in skills required in jobs in that database. Full results of the factor analysis are available from the author.

[10]The factor score is computed as a linear combination of the original skill variables times a weight derived from the factor loading. Factor scores are standardized with a mean of zero, with about two-thirds of the values lying between +1.0 and –1.0 (and a range of approximately +3.0 to –3.0).

The third set of estimations consists of partially specified models using only skills (that is, $\alpha_1 = \alpha_f = 0$) or institutions (that is, $\alpha_s = 0$). Results from these estimations indicate whether or not the results are sensitive to model specification by comparing the size and significance of individual α's between the fully and partially specified models. I also compare the R^2 between the models estimated with only institutions and those estimated using only skills to gain a sense of the relative importance of institutions and skills.[11] Finally, because research has focused on the capacity of unions to increase wages in low-skill jobs (DiNardo, Fortin, and Lemieux 1996), I estimate unions' influence using R^2 change, measured as the difference between the R^2 obtained from an estimation using only nonunion institutional variables ($\alpha_1 = \alpha_s = 0$) and the one obtained using only institutional variables ($\alpha_s = 0$). The higher the incremental R^2, the stronger the presumed influence of unions on wage determination in low-skill jobs.

To structure the interpretation of the analysis, I categorize skills into (a) new basics and (b) physical or mechanical, consistent with research showing new basic skills increasingly tied to wages (Murnane, Willett, and Levy 1995) and alterations in the use of physical and mechanical skills induced by skill-biased technology change (Bartel, Ichniowski, and Shaw 2003). Most of the BALS and O*NET skills fall into these categories. In fact, only three of the 22 factor-analysis–defined skills seem to fall outside them.

Results

Both national and local databases tell the same story about low-skill positions: jobs are concentrated in a few occupations and require a relatively large number and variety of skills. At least two-thirds of all jobs available to workers with a high school education or less fall into six occupational categories, although they comprise only about one-third of all jobs in the United States (Table 1): food preparation and serving; building and grounds cleaning/maintenance; sales; office/administrative support; production; and transportation and material moving. These jobs require a relatively large number and variety of skills—new basic, physical, and mechanical.[12] Over three-fourths of the jobs in the BALS and the O*NET databases require oral and written comprehension of English, over half require oral and written expression and deductive reasoning, and at least half require math, reading comprehension, active listening, writing, and speaking. The O*NET low-skill jobs require physical and mechanical skills at relatively high levels. Over 70% require near vision, information ordering, manual dexterity, wrist-finger speed, extent flexibility, arm-hand steadiness, static strength, control precision, multilimb coordination, operation and control skills, and mechanical knowledge. (For explanation of these skills, see the Appendix.) Furthermore, mechanical knowledge and skills, including production and processing, operation and control, equipment maintenance, and 16 physical abilities, comprise a *greater proportion* of all job requirements in job zone 1 jobs than in other jobs.

Although jobs for workers with a high school education or less require a large number and variety of skills, they generally require fewer skills than other jobs. Job zone 1 jobs have lower requirements than all jobs in 21 of the 33 measures of knowledge, 27 of the 35 measures of skills, and 15 of 51 measures of abilities, *all* of which fall into areas that could be classified as new basic skills. While these points of comparison between job zone 1 jobs and all jobs are consistent with wage differentials between educational groups, however, they say nothing about within-group wage differentials for workers with a high school education or less, an issue that

[11]Since the size of the R^2 is a function of the true influence of skills or institutions on wages as well as the constructs used to measure them, such comparisons might be viewed as suspect. I believe the comparison provides some crude additional evidence on how wages are related to skills and institutions.

[12]Results are not shown in a table, but are available from the author. In this analysis use is defined in the O*NET data as a value of three or above on a five-point scale in which 1 = not important and 5 = extremely important.

Table 1. Occupations of Low-Skill Jobs and Individuals.

	All Jobs	Low-Skill Jobs		
Independent Variable	*U.S. National Data, 2001*	*U.S. Population with a High School Education or Less*	*O*NET Job Zone 1 Jobs*	*BALS Jobs*
Occupational Category				
Food Preparation and Serving	2.1	8.7	6.7	8.2
Building and Grounds Cleaning/Maintenance	1.2	6.5	2.2	8.4
Sales and Related	2.7	11.9	4.4	12.1
Office/Administrative Support	7.3	14.8	14.8	33.1
Production	14.5	13.9	34.1	12.1
Transportation and Material Moving	6.8	10.2	13.3	10.6
% Total Employment Opportunities	34.6	66.0	75.5	84.5
N	—	74,741,962	135	405

Notes: Numbers represent the percentage of workers (column 3) or jobs (columns 2, 4, and 5) in each occupational category. An occupational category was included in the table if more than 5% were low-skilled in at least two of the three databases of low-skilled workers/jobs. Data on the distribution of *All Jobs* (in 2001) are taken from Occupational Employment Statistics (OES) data (survey of establishments) (U.S. Bureau of Labor Statistics 2002) and are based on the number of occupations, not employment, within a firm, consistent with O*NET and the BALS data. Data on *U.S. Population with a High School Education or Less* are from the U.S. Census 2000 Public Use Microdata Sample (PUMS), the one percent sample (U.S. Bureau of Census 2003).

requires an assessment of the variations in skill requirements in low-skill jobs. One way I test for this variation is through the average factor score in an occupation. A factor score value close to zero suggests that jobs in the occupation use an average level of skills in the skill set, a high positive value suggests more intense use of skills, and a negative score suggests nonuse. Factor score differences across occupations therefore suggest within-group variations in skill requirements. I focus on the six occupations encompassing the majority of low-skill positions.

The analysis shows considerable variation in skills across occupations (Table 2). Both office/administrative support and sales jobs use new basic skills, including clerical, writing, sales, reading forms, arithmetic, problem-solving, and decision-making. Sales and arithmetic skills are used more and office skills are used less in sales jobs than in office/administrative support jobs. Production, maintenance, transportation, and food service jobs demand large motor skills and working with people. Maintenance jobs also require reading instructions, mechanical skills, flexibility of closure, and a basic knowledge of chemistry. Production jobs also require reading forms, measurement, decision-making, small motor skills, production skills, reaction & response, flexibility of closure, and knowledge of science and chemistry. Transportation jobs also require reading instructions and production skills, and food service jobs also require small motor skills, reaction & response, and knowledge of chemistry.

These results suggest that office/administrative support and sales jobs generally require new basic skills, while production, maintenance, transportation, and food service jobs generally require physical or mechanical skills. A question that naturally arises is whether low-skill jobs all fall into the two categories (new basic skills, or physical and mechanical skills). A finding of strong correlations between measures of new basic skills, strong correlations between physical/mechanical skills, and weak correlations between those two groups of skills would support such a dichotomy. Indeed, the Pearson correlation coefficients between factor scores exhibit this pattern (Table 3): 69.2% (54 of 78) of the correlations between new basic skills are positive and significant, as are 66.7% (10 of 15) of the correlations between

Table 2. Occupational Differences in Knowledge, Skills, and Abilities.

	Occupational Category						
Skills	*Food*	*Building/ Grounds/ Maintenance*	*Sales*	*Office/ Admin.*	*Prod.*	*Transp.*	*Other Occupation*
New Basic Skills							
New Basics (O*NET)	–.702	–.942	**.543**	**.563**	–.850	–.957	**.388**
Writing (BALS)	–.635	–.926	**.167**	**.558**	–.648	–.418	**.191**
Report Generation (BALS)	–.415	–.261	–.036	**.206**	–.174	–.287	**.219**
Reading Forms (BALS)	–.462	–.418	**.293**	**.222**	**.168**	**.078**	–.352
Reading Instructions (BALS)	–.146	**.207**	–.010	–.136	–.197	**.592**	–.005
Arithmetic (BALS)	–.134	–.544	**.623**	**.126**	–.014	–.237	–.208
Measurement (BALS)	–.218	**.011**	–.105	–.057	**.111**	–.176	**.303**
Problem-Solving (BALS)	–.443	–.321	**.053**	**.189**	–.287	–.146	**.211**
Decision-Making (BALS)	**.075**	–.332	**.190**	**.067**	**.005**	–.070	–.099
Working with Others (BALS)	**.053**	**.380**	–.212	–.177	**.274**	**.275**	–.045
Office (BALS)	–.641	–.717	–.120	**.931**	–.718	–.590	–.229
Clerical (O*NET)	–.846	–1.024	**.157**	**.561**	–.271	–.330	**.027**
Sales (BALS)	**.087**	–.711	**1.030**	**.342**	–1.104	–.443	–.150
Physical and Mechanical Skills							
Large Motor (O*NET)	**.302**	**.898**	–.520	–.785	**.735**	**.710**	**.468**
Small Motor (O*NET)	**.364**	**.086**	**.103**	–.145	**.842**	–.451	–.257
Production (O*NET)	–.351	–.974	**1.097**	–.242	**1.026**	**.201**	–.497
Reaction & Response (O*NET)	**1.022**	–.305	–.494	–.369	**.709**	–.457	**.478**
Flexibility of Closure (O*NET)	–.457	**.008**	–.781	**.107**	**.739**	–.267	**.335**
Mechanical (O*NET)	–1.144	**.440**	–.633	–.299	**.960**	**.628**	**.292**
Other Skills							
Science Knowledge (O*NET)	–.270	–.410	–.434	–.054	**.668**	–.845	**.838**
Chemistry Knowledge (O*NET)	**.133**	**1.461**	**1.110**	–.620	**.081**	–.596	–.014
Public Safety & Security (O*NET)	–.180	–.422	**1.525**	–.491	–.171	–.253	**.379**
N	32	32	50	130	42	42	73

Notes: Data are from the BALS or the O*NET. The O*NET data were linked to the BALS jobs through the SOC-O*NET code. Numbers represent the average factor score in each occupation. Skill information was not available for three occupations in the BALS and six occupations drawing on the O*NET. Positive factor scores are flagged by **bold**.

skills in the physical/mechanical set, whereas 87.2% (68 of 78) of the correlations between new basic and physical/mechanical skills are either negative and statistically significant or not statistically significant. Particularly high (> .4) correlations exist between the writing and office, sales, and problem-solving skills; between sales and office skills; between arithmetic and reading forms; and between office and clerical skills.[13] The categorization of skills suggested by these patterns will help structure the interpretation of the estimation results.

Do the new basic or physical/mechanical skill requirements explain wage variation in low-skill jobs? A cursory look at the BALS data suggests that although considerable wage variation exists in low-skill jobs, its pattern is not necessarily determined by skill requirements. Wages in the BALS jobs vary from $5.15 to $24.07 per hour, with 4% of jobs paying more than $16.11 per hour (the equivalent of earning the national median income of $33,500 for full-time work). Wage variation exists both within and between occupations (Table 4). Twelve percent of the BALS jobs pay more than $13.00, but only

[13]Working with others and knowledge of science show little pattern in their correlation with other skills, while chemistry knowledge is often negatively correlated with new basic skills and public safety knowledge is positively correlated with new basic and physical and mechanical skills.

Table 3. Skills Correlations.

	A. New Basic Skills												
Skill	*New Basics*	*Writing*	*Report Generation*	*Reading Forms*	*Reading Instructions*	*Arith-metic*	*Measure-ment*	*Problem-Solving*	*Decision-Making*	*Working with Others*	*Office*	*Clerical*	*Sales*
New Basics													
Writing (BALS)	**0.531**	1.000											
Report Generation (BALS)	**0.147**	**0.154**	1.000										
Read Forms (BALS)	**0.119**	**0.204**	**0.195**	1.000									
Read Instructions (BALS)	–0.027	**0.129**	**–0.100**	–0.044	1.000								
Arithmetic (BALS)	**0.154**	**0.291**	**0.154**	**0.404**	0.086	1.000							
Measurement (BALS)	0.056	**0.199**	–0.029	0.005	**0.242**	**0.223**	1.000						
Problem Solving (BALS)	**0.225**	**0.401**	**0.207**	**0.189**	0.088	**0.232**	**0.282**	1.000					
Decision Making (BALS)	**0.108**	**0.196**	0.014	**0.125**	**0.126**	**0.244**	**0.106**	**0.235**	1.000				
Working with Others (BALS)	**–0.181**	0.017	–0.080	0.058	**0.264**	0.087	**0.122**	**0.100**	0.006	1.000			
Office (O*NET)	**0.511**	**0.542**	**0.189**	**0.137**	0.031	**0.231**	**0.136**	**0.301**	**0.119**	**–0.107**	1.000		
Clerical (O*NET)	**0.396**	**0.271**	**0.116**	**0.175**	–0.076	**0.198**	0.047	**0.197**	0.063	–0.095	**0.327**	1.000	
Sales (O*NET)	**0.467**	**0.512**	**0.153**	**0.147**	0.015	**0.241**	0.07	**0.309**	**0.194**	–0.083	**0.197**	**0.163**	1.000
Physical and Mechanical													
Large Motor (O*NET)	**–0.395**	**–0.350**	**–0.123**	**–0.106**	**0.185**	**–0.190**	0.067	–0.095	–0.052	0.088	**–0.553**	–0.088	**–0.403**
Small Motor (O*NET)	**–0.103**	**–0.258**	**–0.147**	–0.022	0.018	–0.046	0.000	**–0.181**	–0.038	0.024	**–0.242**	**0.218**	**–0.190**
Reaction & Response (O*NET)	**–0.193**	–0.083	0.014	–0.082	0.014	–0.024	0.034	0.069	0.044	0.071	**–0.250**	0.094	–0.044
Production (O*NET)	–0.055	**–0.146**	**–0.101**	**0.176**	–0.021	**0.240**	0.036	**–0.103**	**0.103**	0.018	**–0.120**	**0.155**	–0.052
Flexibility of Closure (O*NET)	–0.003	–0.058	**0.126**	–0.028	–0.020	**–0.140**	–0.028	0.017	**–0.109**	0.002	0.019	**0.209**	**–0.225**
Mechanical (O*NET)	**–0.100**	**–0.155**	–0.076	0.003	**0.136**	**–0.148**	**0.133**	0.032	–0.060	0.029	**–0.219**	**0.102**	**–0.404**
Other													
Science Knowledge (O*NET)	**0.113**	–0.005	0.035	**–0.138**	**–0.125**	–0.006	**0.113**	–0.001	0.017	–0.029	0.039	**0.127**	**–0.112**
Chemistry Knowledge (O*NET)	**–0.130**	**–0.265**	**–0.145**	–0.036	0.064	0.092	0.084	–0.085	0.006	0.046	**–0.291**	**–0.108**	–0.060
Public Safety & Security (O*NET)	**0.144**	0.054	–0.003	0.055	0.032	**0.101**	–0.016	0.055	0.046	–0.056	**–0.205**	**0.289**	**0.207**

Continued

Table 3. Continued.

B. Physical, Mechanical, and Other Skills

Skill	*Large Motor*	*Small Motor*	*Reaction & Response*	*Production*	*Flexibility of Closure*	*Mechanical*	*Science*	*Chemistry*
Physical and Mechanical								
Small Motor (O*NET)	**0.362**	1.000						
Reaction & Response (O*NET)	**0.306**	**0.181**	1.000					
Production (O*NET)	–0.034	**0.207**	**–0.126**	1.000				
Flexibility of Closure ((O*NET)	**0.201**	**0.310**	**0.228**	0.037	1.000			
Mechanical (O*NET)	**0.475**	**0.262**	0.045	–0.02	**0.234**	1.000		
Other								
Science Knowledge (O*NET)	**–0.102**	0.032	0.067	–0.091	**0.101**	0.074	1.000	
Chemistry Knowledge (O*NET)	**0.111**	**0.194**	–0.015	**0.438**	**–0.158**	0.005	**–0.153**	1.000
Public Safety & Security (O*NET)	**0.170**	**0.266**	**0.203**	**0.179**	0.048	**0.185**	0.003	**0.225**

Notes: Data are from the BALS or the O*NET. The O*NET data were linked to the BALS jobs through the SOC-O*NET code. Numbers reflect the Pearson correlation coefficients between the different measures of skills. Correlations with statistical significance at the 5% level are flagged by bold.

Table 4. Wage Distribution, Occupations, and Skills.

Wages	***All Jobs***	***New Basic Skills***		***Physical and Mechanical Skills***				
		Office	*Sales*	*Production*	*Transpor-tation*	*Building/ Grounds/ Main-tenance*	*Food Services*	*Other Occupation*
% Low ($5.15–$7.87)	33.0	21.1**	56.3**	29.2	20.9	29.4	75.8**	31.2
% Middle ($8.00–$9.97)	30.3	24.1	22.9	43.8	44.2	32.4	18.2	34.4
% High ($10.00+)	36.8	54.9**	20.8**	27.1	34.9	38.2	6.1**	34.4
% Top 12% ($13.00+)	12.0	14.3	2.1**	12.5	11.6	20.6	3.0**	14.8
Mean Wage	$9.44	$10.21**	$8.06**	$9.10	$9.70	$9.88	$7.34**	$9.83
(standard deviation)	(3.00)	(2.68)	(1.76)	(2.66)	(3.45)	(3.24)	(1.63)	(3.85)
N	405	133	50	43	42	32	32	73

Note: Data are from the BALS database.
**Significant (p ≤ .05) differences exist between all jobs and each occupation, as determined by a t-test.

2.1% of sales and 3% of food service jobs pay at this level. Thirty-three percent pay between $5.15 and $7.87 per hour, a percentage that rises to 56.3% of sales jobs and 75% of food service jobs and falls to 21.1% of office/administrative support jobs. Sales positions pay $2.15 per hour less than office/administrative support positions, even though both use new basic skills, and food service positions pay about $1.00 per hour less than positions in other occupations using physical skills.

OLS estimation of equation (1) helps explain why descriptive statistics do not present a patterned wage-skills relationship: both institutions—in the form of industry and unionization—and skills influence wages (Table 5). Although there is no statistically significant relationship between firm size and wages in the low-skill position, wages are higher when a union represents the incumbent worker and lower when the job is in an industry with a relatively high percentage of low-skill jobs (that is, one of the industries represented by binaries in the analysis).[14] The R^2 change upon removal of the union variable from the estimation containing only institutions suggests that about one-third of the institutional influence on wages is through unions (.081/.259).

These results suggest that skills also influence wages, although the influence is not always positive. As a general conclusion, the results suggest that wages are higher in jobs using new basic, office/clerical, or mechanical skills and lower in jobs using physical skills. In all estimations, both those that are fully specified and those with only skill variables included, wages in low-skill jobs are higher if the jobs require mechanical, writing, or office skills. Other skills significantly predict wages in estimations using fewer skill constructs (that is, estimations using only the BALS or the O*NET skill measures), suggesting that the relatively high correlations between the measures of new basic skills shown in Table 3 might make it difficult to achieve significance (p ≤ .05) when estimations include all skill measures. In estimations using only the BALS or the O*NET skill measures, new basic, clerical, and reading instruction skill measures are positive and statistically significant predictors of wages. Jobs requiring physical skills (small motor, reaction & response, production) have statistically significantly lower wages, with results varying little across estimations. Two skills run counter to the general statement that wages are higher in jobs requiring new basic skills and lower in jobs requiring physical skills: lower wages are associated with jobs using sales skills, perhaps because they pay tips or commissions; and higher wages are found in jobs requiring

[14]The omitted category for the industry binaries is firms in industries with less than 6.5% of the low-skill jobs. These industries are wholesale trade, finance, insurance and real estate, public administration, transportation, communication and public utilities, construction, agriculture, and mining. Industries measured by the binary variables account for 76% of the BALS low-skill jobs.

Table 5. Skills, Institutions, and Wages in Low-Skill Jobs.

Variable	*Estimations with Skills and Institutions*			*Estimations with Skills Only*			*Estimations with Institutions Only*	
	All Skill Measures	*BALS Skills*	*O*NET Skills*	*All Skill Measures*	*BALS Skills*	*O*NET Skills*	*All Institutions*	*Institutions without Union*
Skills								
New Basics								
New Basics (O*NET)	.009	—	.039***	.011	—	.039**	—	—
Writing (BALS)	.044***	.045***	—	.057***	.062****	—	—	—
Report Generation (BALS)	.017	.019	—	.029**	.036***	—	—	—
Reading Forms (BALS)	–.002	–.002	—	–.000	.003	—	—	—
Reading Instructions (BALS)	.013	.026**	—	.020	.032**	—	—	—
Arithmetic (BALS)	.018	.006	—	.015	–.003	—	—	—
Measurement (BALS)	.016	.014	—	.014	.018	—	—	—
Problem-Solving (BALS)	–.003	.015	—	–.004	.018	—	—	—
Decision-Making (BALS)	–.010	–.018	—	–.005	–.015	—	—	—
Working with Others (BALS)	.011	.010	—	.022	.018	—	—	—
Office (BALS)	.093****	.090****	—	.092****	.098****	—	—	—
Clerical (O*NET)	.020	—	.048****	.022	—	.054****	—	—
Sales (BALS)	–.035**	–.058****	—	–.058***	–.095****	—	—	—
Physical and Mechanical								
Large Motor (O*NET)	.037**	—	.003	.051***	—	.023	—	—
Small Motor (O*NET)	–.028**	—	–.038***	–.040***	—	–.060****	—	—
Production (O*NET)	–.045***	—	–.048***	–.029	—	–.035**	—	—
Reaction & Response (O*NET)	–.031**	—	–.038***	–.031**	—	–.040***	—	—
Flexibility of Closure (O*NET)	–.012	—	–.005	.019	—	.036**	—	—
Mechanical (O*NET)	.037**	—	.043***	.036**	—	.052****	—	—
Other								
Science Knowledge (O*NET)	–.008	—	–.015	–.006	—	–.012	—	—
Chemistry Knowledge (O*NET)	.023	—	.009	.026	—	.012	—	—
Public Safety & Security (O*NET)	–.015	—	–.036**	–.033**	—	–.063****	—	—
Institutions								
Firm Size								
Small Firm	–.018	–.004	–.022	—	—	—	–.008	–.043
Large Firm	.043	.037	.063	—	—	—	.052	.082**
Industry (Omitted Category: Industries with < 6.5% of Low-Skill Jobs)								
Services	–.085**	–.081**	–.094**	—	—	—	–.119***	–.159****
Manufacturing	–.025	–.088**	–.051	—	—	—	–.158****	–.161****
Retail Trade	–.103***	–.140****	–.144****	—	—	—	–.246****	–.283****
Business Service	–.108***	–.079	–.099***	—	—	—	–.077	–.131***
Education and Medicine	–.082**	–.077	–.079	—	—	—	–.055	–.046
Union	.204****	.203****	.209****	—	—	—	.203****	—
Intercept	2.204	2.215	2.212	2.199	2.201	2.199	2.250	2.331
R^2	.499	.417	.384	.346	.272	.204	.259	.178
F 11.34	14.03	12.15	8.82	13.07	8.89	16.90	12.12	
N 387	393	390	390	396	394	396	400	

Notes: Data are from the BALS or the O*NET. The O*NET data were linked to the BALS jobs through the SOC-O*NET code. Numbers represent the coefficients from OLS estimations of equation (1). The Appendix defines the variables. Full results are available from the author on request.

**Statistically significant at the .05 level; ***at the .01 level; ****at the .001 level.

large motor skills, although this result occurs only in estimations using both the BALS and the O*NET skill measures, suggesting that it might be spurious correlation.

R^2 comparisons between the estimations show a similar percentage of wage variation explained in estimations from (1) models using only the BALS or the O*NET skill measures and (2) partially specified models. Although the R^2 is higher in models (only) using BALS-measured skills than in those using O*NET-measured skills, the differences are small: .068 with partially specified models and .033 with fully specified ones. Comparisons between the partially specified models show that the R^2 of institution-only estimations (.259) falls in-between the R^2 of skill-only estimations (.346 with all skill measures and .204 with only O*NET measures), additional evidence that both skills and institutions influence wages in jobs for workers with little education.

Summary and Discussion

This examination of the influence of specific skills and institutions on wages in low-skill jobs in one local labor market improves our understanding of the forces that determine wage differentials within the low-skilled population. It also contributes methodologically, by illustrating how skill measures developed from a national database (O*NET) can be linked to data from a local labor market database that lacks skill information.

The results indicate that both skills and institutions determined wages in jobs for workers with a high school education or less. Variables that were positively associated with wages in BALS jobs were (1) inclusion of new basic, office/clerical, or mechanical skills among the job requirements, (2) union representation for the job incumbent, and (3) location of the job in an industry with relatively few low-skill jobs. Negatively associated with wages were physical skill requirements and location of the job in an industry with a relatively high proportion of low-skill jobs. While the data do not reveal why some skills and institutions were associated with higher wages and others with lower wages, they provide insights into what factors created wage differentials in positions for individuals with a high school education or less.

The skills that were positively associated with wages in jobs for workers with a high school education or less were those—new basic skills and mechanical skills—that required an investment, while the skills that were negatively associated with wages were more innate and physical. Hence, wages should increase for individuals with low levels of education who gain new basic and mechanical skills at levels required in low-skill jobs. For some individuals with a high school education or less, raising skills to levels needed in low-skill jobs might be a long-term investment. For these individuals, access to low-skill jobs paying relatively high wages may come from labor market institutions. Although the more highly skilled of the low-wage workers are more likely to be placed in high-wage firms (Holzer, Lane, and Vilhuber 2004), the correlation is not perfect, and the "luck of the draw"—including employment in an area with supportive institutions—comes into play.

Of course, given the case study nature of this research, the findings reported here might not extend beyond the local labor market I have examined. Indeed, the strength of unions in the San Francisco Bay Area might overstate their importance for wage-setting in other areas of the country. In this respect, the study's findings might be better viewed as highlighting the *potential* for unions to increase wages of workers who have neither education nor skills than as measuring unions' current influence on wages outside the study area. Another caveat is that several factors not included in this study could help explain wage variation in jobs available to individuals with a high school education or less. Jobs with high proportions of women or minorities might have reduced wages, as occupational segregation—whether through self-selection or through discrimination—increases labor supply and decreases wages. Furthermore, these job characteristics may be correlated with skills, adding another layer of complexity to the explanation for wage variation in jobs for low-skilled workers. Finally, more fine-tuned measures of institutions, including indicators of high-performance workplace practices, might increase the explanatory power of labor market institutions in specifications designed to predict wages in low-skill positions. While the data at hand do not allow testing of these propositions, the study's results provide food for thought about what forces might determine whether an individual with a high school education or less can earn a wage high enough to stay out of poverty.

Appendix
Definitions of Variables Used in the Multivariate Analysis

Variable	*Definition*
Dependent Variable	
Log Wage	Log of starting hourly rate of pay in position (average if the position pays a range).
Independent Variables	
New Basic Skills	
New Basics	The factor score from a factor analysis of O*NET skills, which is linked to BALS jobs through the SOC-O*NET code. Skills loading high include social perceptiveness, speaking, speech clarity, oral expression, critical thinking, speech recognition, active listening, service orientation, judgment and decision-making, writing, time management, customer and personal service, coordination, active learning, oral comprehension, English language, inductive and deductive reasoning, problem sensitivity, reading comprehension, far vision, time sharing, monitoring, written expression, selective attention, transportation, mathematics ability and knowledge, complex problem-solving, written comprehension, public safety and security, memorization, near vision, flexibility of closure, mathematical reasoning, and clerical.
Writing	The factor score from a factor analysis of the BALS skills needed in the job. Skills loading high include reading written instructions, manuals, general memos, letters, and forms; writing simple sentences and paragraphs, short notes, simple memos or accurate telephone messages; completing forms, logs, charts, or labels; using complex telephone systems; and choosing words and manner of expression appropriate to the workplace.
Report Generation	The factor score from a factor analysis of the BALS skills needed in the job. Skills loading high include writing letters using correct structure and sentence style; proofreading; organizing information into a brief report; evaluating results; and reading contracts and agreements.
Reading Forms	The factor score from a factor analysis of the BALS skills needed in the job. Skills loading high include reading shipping labels, logs/journals, invoices/work orders, and forms.
Reading Instructions	The factor score from a factor analysis of the BALS skills needed in the job. Skills loading high include reading maps, safety warnings, product labels, and manuals.
Arithmetic	The factor score from a factor analysis of the BALS skills needed in the job. Skills loading high include performing addition, subtraction, multiplication, or division; using ratios, fractions, decimals, or percents; estimating or rounding off numbers; solving simple equations; using business equipment (for example, calculator, cash register, business machine); and making change.
Measurement	The factor score from a factor analysis of the BALS skills needed in the job. Skills loading high include performing simple measurements and using measurement instruments.
Problem-Solving	The factor score from a factor analysis of the BALS skills needed in the job. Skills loading high include prioritizing tasks; gathering information; sorting and categorizing information; identifying work-related problems, potential solutions to problems, and barriers to solutions; and implementing solutions and evaluating results.
Decision-Making	The factor score from a factor analysis of the BALS skills needed in the job. Skills loading high include working in teams/collaboratively solving problems; making decisions independently; and implementing solutions (to problems).
Working with Others	The factor score from a factor analysis of the BALS skills needed in the position. Skills loading high include being perceptive of verbal and nonverbal cues from others, and interacting with coworkers to accomplish a task.
Office	The factor score from a factor analysis of the BALS skills needed in the job. Skills loading high include proofreading; making and receiving business phone calls; using tele phone systems, answering machines, copiers, faxes, computers with Windows operating systems, word processing and spreadsheet software, and email; taking telephone messages accurately; and writing letters using correct structure and sentence style.
Clerical	The factor score from a factor analysis of O*NET skills, which is linked to BALS jobs through the SOC-O*NET code. Skills loading high include number facility, mathematical reasoning, information ordering, near vision, written expression, perceptual speed, written comprehension, clerical, wrist-finger speed, category flexibility, and deductive reasoning.
Sales	The factor score from a factor analysis of the BALS skills needed in the job. Skills loading high include making change; taking telephone messages accurately; dealing with cus-

Continued

Appendix ***Continued***

	tomers; explaining products and services; handling complaints; selling a product or service; and using business equipment (for example, calculator, cash register, business machine).
Physical and Mechanical Skills	
Large Motor	The factor score from a factor analysis of O*NET skills, which is linked to BALS jobs through the SOC-O*NET code. Skills loading high include gross body coordination; spatial orientation; static, explosive, and dynamic strength; stamina; multilimb coordination; speed of limb movement; depth perception; trunk strength; dynamic and extent flexibility; rate control; response orientation; reaction time; visual color discrimination; manual dexterity; engineering; technology; mechanical and chemistry knowledge; control precision; and public safety and security.
Small Motor	The factor score from a factor analysis of O*NET skills, which is linked to BALS jobs through the SOC-O*NET code. Skills loading high include manual dexterity, arm-hand scale, finger dexterity, visualization, perceptual speed, and category flexibility.
Production	The factor score from a factor analysis of O*NET skills, which is linked to BALS jobs through the SOC-O*NET code. Skills loading high include mathematics knowledge and abilities, production processes, and processing abilities.
Reaction & Response	The factor score from a factor analysis of O*NET skills, which is linked to BALS jobs through the SOC-O*NET code. Skills loading high include auditory attention, reaction time, and response orientation.
Flexibility of Closure	The factor score from a factor analysis of O*NET skills, which is linked to BALS jobs through the SOC-O*NET code. Skills loading high include flexibility of closure, defined as the ability to identify or detect a known pattern (a figure, object, word, or sound) that is hidden in other distracting material.
Mechanical	The factor score from a factor analysis of O*NET skills, which is linked to BALS jobs through the SOC-O*NET code. Skills loading high include installation, equipment maintenance, repairing, troubleshooting, operation monitoring, operation and control, equipment selection, quality control analysis, mechanical, engineering and technology, control precision, science knowledge, and visualization.
Other Skills	
Science Knowledge	The factor score from a factor analysis of O*NET skills, which is linked to BALS jobs through the SOC-O*NET code. Skills loading high include knowledge of science, complex problem-solving, quality control analysis, and monitoring abilities.
Chemistry Knowledge	The factor score from a factor analysis of O*NET skills, which is linked to BALS jobs through the SOC-O*NET code. Skills loading high include knowledge of chemistry.
Public Safety & Security	The factor score from a factor analysis of O*NET skills, which is linked to BALS jobs through the SOC-O*NET code. Skills loading high include knowledge of public safety and security policies, defined as knowledge of relevant equipment, policies, procedures, and strategies to promote effective local, state, or national security operations for the protection of people, data, property, and institutions.
Firm Size	
Small Firm	A 0, 1 binary variable with 1 indicating a firm with 50 or fewer employees.
Large Firm	A 0, 1 binary variable with 1 indicating a firm with 300 or more employees.
Industry (omitted category: industries with < 6.5% of low-skill jobs)	
Service	A 0, 1 binary variable with 1 indicating a firm in the service sector (1987 SIC of 70–72, 74–79, 81, 83–86, 88–89).
Manufacturing	A 0, 1 binary variable with 1 indicating a firm in the manufacturing sector (1987 SIC of 20–40).
Retail Trade	A 0, 1 binary variable with 1 indicating a firm in the retail sector (1987 SIC of 52 to 60).
Business Service	A 0, 1 binary variable with 1 indicating a firm in the business service sector (1987 SIC of 73 or 87, which includes engineering, accounting, research, management, and related services as business services).
Education and Medicine	A 0, 1 binary variable with 1 indicating a firm in the education or medical sector (1987 SIC of 80 or 82).
Union	A 0, 1 binary variable with 1 indicating that the incumbent in the position is represented by a union.

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