Two Sides of the Same Coin

U.S. "Residual" Inequality and the Gender Gap

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ABSTRACT

We show that the narrowing gender gap and the growth in earnings inequality are consistent with a simple model in which skills are heterogeneous, and the growth in skill prices has been particularly strong for skills with which women are well endowed. Empirical analysis of DOT, CPS, and NLSY79 data finds evidence to support this model. A large increase in the prices of cognitive and people skills—skills with which women are well endowed—and a decline in the price of motor skills account for up to 40 percent of the rising inequality and 20 percent of the narrowing gender gap.

I. Introduction

Two major developments have characterized the U.S. labor market since 1970: the dramatic rise in income and wage inequality and the narrowing of the male-female wage gap. Two important literatures have sprung up to investigate the degree to which the rise in income and wage inequality and the narrowing of the wage gap can be attributed to changes in the returns to skills.[1] They find that

1. See Altonji and Blank (1999) for a survey of the gender gap literature and Katz and Autor (1999) for a survey of the inequality literature.

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higher returns to skills can help explain the rise in wage inequality but should have *widened* the gender wage gap (for example, Blau and Kahn 1997). We show that both phenomena are consistent with a simple model in which skills are heterogeneous and the growth in skill prices has been particularly strong for skills with which women tend to be endowed. Empirical analysis of the Dictionary of Occupational Titles (DOT), the Current Population Survey (CPS), and the National Longitudinal Survey of Youth 1979 (NLSY79) data over the period 1968–90 finds evidence to support a model in which skills are heterogeneous within education, experience, and other standard explanatory variables.

Our analysis moves beyond the usual measures of workers' skills such as education and experience by making use of DOT, CPS, and NLSY79 to characterize several types of worker skills. DOT measures a large number of skills that are required to perform over 12,000 occupations in the U.S labor market. Assuming that workers are assigned to jobs in some sort of hedonic market clearing process, we can infer workers' skills from the occupation in which they are employed. We use this hedonic imputation to characterize the workers' cognitive, motor, and people skills as well as physical strength. We then match the DOT data with both the CPS and NLSY79 data to identify workers' wages and other individual characteristics.

We find that the wage returns to cognitive and people skills more than doubled during the 1968–90 period, with the distinction that people skills became more valuable by being complementary to other skills. In the same period, the wage return to motor skills declined by 60 percent and the return to physical strength did not change in a statistically significant way. We also find that within educational groups the top of the wage distribution was in cognitive- and people-intensive occupations while the bottom was in motor-intensive occupations. Therefore, the estimated changes in skill prices can help explain the increase in residual inequality observed in the United States. Such estimated changes in skill prices can also help explain the narrowing of the gender wage gap, since we find that by 1980 females were in more cognitive- and people-intensive occupations relative to males. To be more concrete, changes in wage returns to cognitive, motor, and people skills as well as physical strength accounted for 20–40 percent of the observed changes in residual inequality for different education groups and for around 20 percent of the narrowing in the gender gap.

Our findings add to different literatures, such as the aforementioned that aim to identify the sources of rising inequality and the narrowing of the gender gap in the United States in the 1970s and 1980s. These wage inequality and wage gap literatures find a widespread increase in the demand and price of skills in the 1980s, which led to changes in the wage structure that raised inequality (for example, Bound and Johnson 1992; Katz and Murphy 1992; Juhn, Murphy, and Pierce 1993; and others) and widened the gender pay gap (for example, Blau and Kahn 1997). In contrast, our analysis shows that some skills became more valuable while others became less valuable in the 1970s and 1980s and that these skill price changes can help explain both the rising inequality and the narrowing of the gender gap.

Our paper also relates to a literature that proposes a task-based approach to understand the labor market effects of technological changes (for example, Acemoglu 2002; Autor, Levy, and Murnane 2003). This literature uses data similar to ours but focuses on categorizing skills as being useful to produce routine versus nonroutine tasks. For instance, Autor, Levy, and Murnane (2003) use the DOT variable *fingdex* (finger dexterity) as a measure of routine manual tasks and the DOT variable *eye-hand* (eye-hand-foot coordination) as a measure of nonroutine manual tasks. We instead argue that the *fingdex* and *eyehand* variables (along with seven others) capture different aspects of the motor/manual skills required to perform an occupation and thus categorize them under the broad umbrella of *motor skills required to perform an occupation*. We do the same to capture the different aspects of cognitive and people skills. Interestingly, we find that the wage returns of the seven variables that we believe capture different aspects of cognition significantly increased over the period covered in our sample. The wage returns of all the nine DOT measures that capture aspects of motor/manual abilities either did not change in value or became less valuable during the same period. Finally, the wage returns on the four variables that we believe capture aspects of workers' people skills also increased during the period, although some of them in a statistically nonsignificant way.

One recent paper in the task-based literature that particularly relates to ours is Black and Spitz-Oener (2007). It builds on our analysis by using the Qualification and Career Survey, a German data set where workers self-report tasks they perform in their jobs. The authors use these self-reported measures to study if changes in the tasks performed by males and females and their associated prices explain the closing of the gender pay gap in Germany. Some of their findings are similar to ours while others are different. They find that changes in the tasks performed within occupations explain a large part of the narrowing of the gender gap in Germany. We also find that changes in observed job and individual characteristics explain a large part of the narrowing of the gender gap in the United States (for example, Blau and Kahn 1997). However, they find that changes in task prices contributed to widening the gender gap in Germany while we find that such task-price changes contributed to narrowing the gender gap in the United States. A number of reasons may account for the different results. First, the U.S. and German labor markets may have been affected by different economic forces. Indeed, this seems to be the case since most of the narrowing of the gender gap happened in the United States in the 1980s (Blau and Kahn 1997, 2006) and in Germany in the 1990s (Black and Spitz-Oener 2007). Second, the skill measures that Black and Spitz-Oener use are significantly different than ours, with their measures focusing on the routine versus nonroutine aspects of jobs. Finally, the occupation classification in their data set is more aggregated than ours, containing only around 80 occupations. If the employment composition of males and females was changing differently within their broadly defined occupations, task-price estimates and their effects on the gender pay gap might suffer from aggregation bias. Of course, only a more detailed analysis of the two data sets can identify the sources of the different findings.

Our results also relate to the findings of Borghans, ter Weel, and Weinberg (2006). Using DOT and similar data sets from the U.K. and Germany, they show that the rising importance of soft skills and their associated prices help explain the wage outcomes of women. We complement their findings by showing that people skills did not become more valuable by themselves but that they made cognitive and motor skills more valuable and that such price changes also affected inequality.

Finally, Welch (2000) argues that, in a model with two skills (brains and brawn), if women are relatively well endowed with brains and the price of brains goes up, then the gender gap will narrow. Also, if brains are less well distributed among workers than brawn, then the rising price of brains can also increase wage inequality. We provide empirical confirmation that the prices of cognitive (brains) and people skills increased relative to the price of motor skills during the period 1968–90 and that such price changes narrowed the gender gap. However, we show that the observed changes in skill prices affected inequality not because some skills were not as well distributed as others but rather because within education and experience groups the top and bottom of the wage distribution were intensive in different skills.

The remainder of the paper is organized as follows. The next section presents the analytical framework, while Section III describes the data sets used. Section IV puts forth the empirical strategy and the main estimation issues, presents the estimated wage returns to skills, and discusses a number of robustness checks. Section V quantifies how much of the observed rise in residual inequality was due to the estimated changes in skill prices, and Section VI measures how much of the observed narrowing of the male-female wage gap was due to skill price changes. The final section concludes.

II. Analytical Framework

Suppose we have for each individual i at time t the following wage equation:

$$(1)\quad \ln w_{it} = Z_{it}'\gamma_t + X_{it}'\beta_t + \varepsilon_{it}$$

where w_{it} is wage earnings, X_{it} is a vector of standard explanatory variables such as gender, race, education, and experience, and β_t is a vector of prices of these explanatory variables. Z_{it} is a vector with the worker's cognitive, people, and motor skills as well as physical strength, while γ_t is a vector of prices of these skills.

We use DOT data to characterize workers' physical strength and cognitive, motor, and people skills, and CPS and NLSY79 data to obtain workers' wages and other individual characteristics. We then use Equation 1 to estimate the price vectors β_t and γ_t. In our preferred specification, we pool together all workers in our sample and thus assume that labor markets are not segmented. As we discuss in detail in Section VI, our preferred specification is different than the preferred specification in Blau and Kahn (1997).

Once we have estimates for β_t and γ_t, we implement the full distributional accounting framework as proposed in Juhn, Murphy, and Pierce (1993). Thus, we rewrite Equation 1 as:

$$(2)\quad \log w_{it} = \{X_{it}\overline{\beta} + Z_{it}\overline{\gamma}\} + \{X_{it}(\beta_t - \overline{\beta})\} + \{Z_{it}(\gamma_t - \overline{\gamma})\} + \{\overline{F^{-1}}(\theta_{it}|X,Z) + (F^{-1}(\theta_{it}|X,Z) - \overline{F^{-1}}(\theta_{it}|X,Z))\}$$

where anything denoted by a bar is the average of that parameter or set of variables over time, θ_{it} is the percentile of individual i at time t in the residual distribution of Equation 1, and F is the cumulative distribution of the residuals in the same equation. In Equation 2, the terms inside the first brackets capture the effects of changes in the explanatory variables, both X_{it} and Z_{it}, on the wage distribution. The term inside the second brackets captures the effects of the estimated changes in β_t (the prices of the standard explanatory variables in X_{it}). The term inside the third brackets captures the effects on the wage distribution of the estimated changes in γ_t (the prices of physical strength as well as cognitive, motor, and people skills). Finally, the terms inside the last brackets capture the effect of changes in the distribution of wage residuals. Note that since our analysis focuses on the effects of changes in the prices of physical strength as well as cognitive, motor, and people skills, we do not separate the effects of changes in unobserved characteristics and their prices.[2]

We apply the decomposition above to simulate the effects of changes in observed characteristics, their prices, and unobserved components on two statistics of the wage distribution, the ratio of the 90th to 10th percentile, and the relative average wage paid to males and females. Previous economic analysis suggests that the narrowing gender gap is particularly surprising given the growth in overall earnings inequality. Changes in the wage structure due to skill prices contributed to rising inequality and widening of the gender gap (for example, Juhn, Murphy, and Pierce 1993; Blau and Kahn 1997). We show that both phenomena are consistent with the simple model above in which skills are heterogeneous within education, experience, and other standard explanatory variables if the growth in skill prices was particularly strong for skills with which women tend to be endowed. The analyses in the next sections provide empirical support for this model.

III. Data

The data we use in this paper brings together information from the Fourth Edition of DOT, the CPS, and the NLSY79. DOT is a database that characterizes the multiple skill requirements of occupations. Matching DOT with CPS and NLSY79 allows us to characterize the skills of workers.

Our approach to identifying individual worker skills follows that of Autor, Levy, and Murnane (2003) and others by supposing that in a labor market equilibrium workers are matched to jobs that require skills they have. To be concrete, a worker currently employed as an engineer knows calculus (indicated in DOT as General Educational Development in Math = 6) while one employed as a janitor lacks the skill of direction, planning, and control (indicated in DOT as *dcp* = no). The hedonic imputation of worker skills from occupations is imperfect, and we thus run a number of robustness checks to investigate in detail the effects such imputation might have on the paper's main results. We should note, however, that it is not at all clear that alternative ways of measuring skills would do a better job. Would a survey of workers' self-reported skills produce a better measure of, for instance, a worker's ability to direct, control, and plan than the judgment of an employer? We turn now to a description of the data and their construction process.

2. Blau and Kahn (1997) separate the effects of changes in unobserved characteristics and their prices in order to decompose changes in gender gap into parts due to changes in gender-specific factors and wage structure.

A. Dictionary of Occupational Titles (DOT)

DOT was first developed in response to the demand of an expanding public employment service for standardized occupational information to support job placement activities. The U.S. Employment Service recognized a need for such information in the mid-1930s, soon after the passage of the Wagner-Peyser Act, which established a federal-state employment service system.

The Fourth Edition of DOT, released in 1977, provides measures of 44 different skills required to perform more than 12,000 detailed occupations in the U.S. labor market. The DOT measures are the result of comprehensive studies by trained occupational analysts of how jobs are performed in establishments across the United States and are composites of data collected from diverse sources. Primarily, U.S. Department of Labor occupational analysts "go out and collect reliable data which is provided to job interviewers so they may systematically compare and match the specifications of employer job openings with the qualifications of applicants who are seeking jobs through its facilities" (U.S. Department of Labor Office of Administrative Law Judges Law Library). For the Fourth Edition of DOT, the U.S. Department of Labor conducted approximately 75,000 on-site job analysis studies and supplemented them with information obtained through extensive contacts with professional and trade associations. The Revised Fourth Edition was released in 1991 and includes data collected throughout the 1980s, which was used to revise the skill requirements of occupations. It also includes new occupations. As a result, information on 1,692 of 12,742 occupations was changed (including some occupations that disappeared from the U.S. labor market), and 761 new occupations were added. These new DOT titles were mostly computer-related jobs. While the main use of DOT information has been for job matching, employment counseling, occupational and career guidance, and labor market information services, several economists have also used it, including Autor, Levy, and Murnane (2003), Wolff (2003), and Ingram and Neumann (2006).

Researchers have noted two main limitations of DOT.[3] First, the definitions of the skill requirements are not consistent across DOT editions, making it harder to combine information from different editions and to perform analyses over longer periods of time. We avoid this difficulty by using only the Fourth Edition of the dictionary and its revision. Second, the DOT requirements are likely to be measured with error and thus should be taken only as a proxy for the actual skill requirements of occupations rather than as exact measures. Section IV pays detailed attention to the possible consequences of measurement errors in the data to the findings of the paper, and we find that the skill price estimates are highly robust to the presence of data mismeasurements.

Finally, one might worry that gender stereotypes regarding the complexity of jobs traditionally held by men versus women could introduce gender bias in the DOT's ratings of occupations. Indeed, Witt and Nahemy (1975) argue for the existence of a gender bias in the ratings of the Third Edition of DOT, published in 1966. However, Miller et al. (1980) examine gender bias in the ratings of occupations in the

3. See Miller et al. (1980) and Spenner (1983).

Fourth Edition of DOT, the one we use in the paper, and find no evidence of gender bias.

1. *Selecting DOT Task Measures: Constructing Skill Measures*

The 44 different measures of skills available in the Fourth Edition of DOT fall into seven clusters: work functions; required General Educational Development (GED); aptitudes needed; temperaments needed; interests; physical demands; and working conditions in the environment. We rescale these seven variables so that higher values denote higher requirements and describe them in Table A-1 of the online Appendix.[4]

It is not possible, of course, to use all the DOT variables simultaneously since multicollinearity makes precise estimation impossible. Instead, we use the textual definitions of the variables to identify four broad skill categories: cognitive skills, fine motor skills, people skills, and physical strength.[5]

We use seven DOT measures to capture the different aspects of cognitive skills. These measures capture the complexity of the job in relation to: data; GED in reasoning, mathematics, and language for the job; and aptitudes for intelligence, verbal, and numeric (see Table A-1 in the online Appendix). For instance, *gedm* measures the mathematical development required for the job. At high *gedm* levels, workers are required to know advanced calculus (for example, engineers and math professors), while at low levels they are required only to know how to perform arithmetic (for example, janitors and stevedores). The variable *data* measures the complexity of the job in relation to data. At high data levels, workers should be able to synthesize and analyze data (for example, editors and economists), while at low levels they are required only to be able to compare and copy data (for example, office messengers and clerks). Clearly, being able to solve sophisticated mathematical problems and analyze data are two different aspects of cognition. To capture the multiple aspects of cognition in a parsimonious way, we construct a cognitive index through factor analysis. Panels A and B of Table A-4 in the online Appendix report results for our principal components analysis to generate a cognitive index (with mean 1 and standard deviation 0.1) using the 1977 DOT and the 1991 DOT. The first factor explains 99.3 percent (1977 DOT) and 100 percent (1991 DOT) of the variation in the seven cognitive variables, with each DOT variable having loadings ranging from 0.83 to 0.95. A higher value on this cognitive index indicates that substantive complexity is involved in carrying out the job.

The first panel in Table 1 reports the top and bottom ten occupations according to the cognitive index. By and large, occupations at the bottom of the cognitive index distribution are dominated by operatives, nonprivate household service workers, and laborers. Laborers include stevedores and lumbermen, operatives include oilers, greasers, drivers, and welders, and nonhousehold service workers include waiters and beauticians. Meanwhile, the top of the cognitive index is primarily com-

4. The online Appendix is available at www. rotman.utoronto.ca/bblum/personal/front.htm.
5. Researchers have used these and similar categories from the 1977 Fourth Edition of DOT. See for example, Miller et al. (1980).

Table 1
Top and Bottom 10 Occupations in the Skill Distribution, DOT

Cognitive Skills		Motor Skills	
Bottom 10	Top 10	Bottom 10	Top 10
Laundry and dry cleaning operatives	Geologists and geophysicists	Bill and account collectors	Physicians and surgeons
Charwomen and cleaners	Physicists	Lawyers and judges	Veterinarians
Oilers and greasers	Chemists	Clergymen	Chiropractors
Telegraph messengers	Mathematicians	Credit men	Artists and art teachers
Longshoremen and stevedores	College professors, natural science	Social and welfare workers	Machinists
Fruit, nut, and vegetable graders and packers	Physicians and surgeons	Boarding and lodging house keepers	Draftsmen
Laborers	Engineers	Religious workers	Technicians
Teamsters	Architects	Authors	Dentists
Fishermen and oystermen	Biological scientists	Guards	Toolmakers and setters
Messengers and office boys	Lawyers and judges	Agents	Jewelers

Strength		People Skills	
Bottom 10	Top 10	Bottom 10	Top 10
Natural scientists	Plumbers and pipe fitters	Toolmakers and setters	Clergymen
Personnel workers	Millwrights	Meat cutters	College professors (psychology)
Music teachers	Farm laborers	Teamsters	College professors (subject not specified)
College professors, social sciences	Plasterers	Bricklayers and masons	Religious workers
Bill and account collectors	Sailors and deck hands	Pattern and model makers	Lawyers and judges
Accountants and auditors	Railroad and car mechanics and repairmen	Railroad and car mechanics and repairmen	College professors (biological sciences)
Geologists and geophysicists	Mine operatives and laborers	Roofers and slaters	College professors (other social sciences)
Chiropractors	Farmers	Millers	College professors (economics)
Marshals and constables	Charwomen and cleaners	Cabinetmakers	Social and welfare workers
Entertainers	Structural metal workers	Engravers	K-12 Teachers

Data are from DOT.

prised of professional workers, including college professors, scientists, managers, officials, and proprietors.

Nine DOT variables capture the different dimensions of the fine motor skill requirements of an occupation: complexity of the job in relation to things; aptitudes for manual dexterity, finger dexterity, motor coordination, eye-hand-foot coordination, spatial and form perception, and color discrimination; and adaptability to situations requiring attainment of standards. For instance, high complexity in relation to *things* indicates that workers are required to set up and adjust machinery and to work it precisely (for example, electricians and machinists). Lower values are assigned to jobs where workers have little or no involvement in selecting appropriate tools or in attainment of standards (for example, accountants and clerks). The other variables measure more specific aptitudes, like finger dexterity and spatial and form perception. As with cognitive skills, we use factor analysis to construct a motor index (with mean 1 and standard deviation 0.1) to capture these different aspects in a parsimonious way. Panels C and D of Table A-4 in the online Appendix show that the first factor explains 84.5 percent (1977 DOT) and 95.4 percent (1991 DOT) of the variation on the nine motor variables. A higher value on the motor skills index indicates a job with greater manual/motor demands.

The second panel in Table 1 reports the top and bottom ten occupations according to the motor index. Occupations at the top of the motor skill index distribution are dominated by craftspeople, draftspeople, technicians (for example, medical and dental), and machinists, all occupations where individuals need high levels of motor coordination and finger dexterity. At the bottom of the motor distribution are lawyers, social workers, and clergy.

We use four DOT variables to capture different aspects of the people skills required by occupations (see Table A-1 of the online Appendix). We discuss these variables in greater detail since they might be more controversial than the cognitive and motor measures discussed in the previous paragraphs. The variable *dcp* assesses if an occupation requires direction, control, and planning of an activity. Clearly, *dcp* captures one element of people skills - the ability to manage. Similarly, the variable *influ* measures whether an occupation requires exerting influence. It therefore captures a different type of interpersonal skill that also somewhat relates to the ability to manage, although in this instance the "management" takes place outside of an authority relationship. To make things more concrete, it is useful to consider some specific occupations. Positions of authority such as financial managers and supervisors are required to engage in direction, control, and planning of activities (*dcp* = yes). However, financial managers and supervisors are not required to exert influence over others (*influ* = no). In contrast, teachers and lawyers are required to have influence over others (*influ* = yes), presumably over schoolchildren in the case of teachers and a jury or judge in the case of lawyers. However, while teachers are also required to direct, control, and plan activities (*dcp* = yes), lawyers are not (*dcp* = no).

The third measure of people skills we use is the variable *depl*. It assesses an occupation's requirements of "adaptability to dealing with people beyond giving and receiving instructions." In our view, *depl* captures the widest range of interactions among workers. The four occupations discussed in the previous paragraph require the ability to deal with people beyond giving and receiving instructions, as do physicians and salespersons (*depl* = yes), while mathematicians, insurance underwriters, and machine operators do not require this skill (*depl* = no).

The last DOT measure of people skills we use is the *people* variable. Different from the previous three variables, the *people* variable attempts to rank the degree of interpersonal interaction required by an occupation (see Table A-1 of the online Appendix). The ranking starts with mentorship being assigned more interpersonal skills than negotiation and then continues moving down to receiving instructions. The scale and structure of the ranking is intended to reflect a progression from simple to complex relations with people, such that each successive rank includes those relations that are simpler and excludes those that are more complex (Miller et al. 1980). While we do not see the ranking as being beyond dispute—does mentorship really require more people skills than negotiation?—we do view the arrangement of the people functions as being hierarchical in a more general sense. For instance, it seems hard to dispute that "instructing" people (*people* = 7) involves a broader set of interactive skills than "taking instructions" (*people* = 1).

We combine the information contained in the four measures of people skills described above using factor analysis to construct an index of the people skills required by each DOT occupation. Panels E and F of Table A-4 in the online Appendix show that the first factor explains 100 percent (1977 DOT and 1991 DOT) of the variation in the four variables of social interaction. This index is our preferred measure of people skills as it captures multiple aspects of social interactions.[6]

The bottom panel in Table 1 shows the top and bottom occupations in terms of people skills. By and large, occupations at the bottom of the people skills index are dominated by operatives and laborers, jobs in which social interaction is clearly minimal. Meanwhile, the top of the people skills index include teachers from kindergarten up to college level, religious and social workers, and lawyers.

The final skill measure we consider is the physical strength required to perform an occupation. Different from the previous three sets of skills, physical strength is well defined and one DOT variable (*streng*) measures it as "the degree of strength requirements of jobs as measured by involvement in standing, walking, sitting, lifting, and carrying." The *streng* variable classifies jobs as sedentary, light, medium, heavy, and very heavy, and is what we use to measure whether an occupation requires physical strength. One difficulty with this variable is that it might have a nonmonotonic relationship with wages. Should occupations that are light in terms of their strength requirements command higher wages than ones classified as sedentary? Indeed, we find that on average workers are paid a premium to be in sedentary occupations as well as in occupations that are heavy and very heavy. We deal with this issue by transforming the *streng* variable into a dummy variable that equals one if the occupation is considered heavy or very heavy and zero otherwise. Thus, we distinguish occupations that require above average physical strength from the others.

6. Three other DOT variables may potentially measure aspects of people skills: fif, sjc, and talk (see Appendix Table A-1). We also construct a second index of people skills using these variables and find that all the paper's results hold when we use this alternative measure.

The final panel in Table 1 shows occupations that require and do not require physical strength. Plumbers, farm laborers, and sailors are clearly occupations in which heavy to very heavy physical demands are required. On the other hand, scientists, personnel workers, and music teachers are occupations without heavy physical demands.

B. Current Population Survey

Our wage and employment data come from the March CPS 1968–90 (CPS Utilities 2001). Although CPS is available prior to 1968 and after 1990, the census occupation and industry codes for years before 1968 are too coarse for our purposes and the last DOT was published in 1991. Our sample includes employed individuals aged 18–64 who were not living in group quarters, were not in school, were not working without pay, had a positive number of years of potential labor market experience, had nonmissing occupational responses, and had earned at least three full-time months of minimum wage or above during that year. We also impute earnings for workers top-coded by the census as 1.5 times the top-code value. All wages are deflated by the CPI for All Urban Consumers, with base year 1982–84. The results of the paper are not qualitatively sensitive to the imputation outlined and to the wage measure used (weekly versus annual). We report results using weekly earnings.

We match DOT job skills from the 1977 Fourth Edition to workers in the March CPS surveys from 1968 to 1977. For workers in the March CPS 1978–91, their DOT job skills come from the 1991 Revised Fourth Edition of DOT. As discussed above, both the 1977 and 1991 DOTs scored more than 12,000 occupations. However, as with most surveys, CPS does not code to such a detailed occupational classification (only about 450). To map DOT codes to census occupation codes, we utilize a special version of the April 1971 CPS issued by the National Academy of Sciences (2001), in which a committee of experts assigned individual DOT occupation codes and measures to the 60,441 workers in the sample. We then compute the DOT skill requirements of each census occupation as the weighted mean of the skill requirement of the DOT occupations in that census occupation using CPS sampling weights by occupation, industry, and gender.

Finally, we create a uniform occupation coding scheme across the period 1968–90 to merge the skill requirements of occupations to each job in the CPS. The 1 percent census samples (IPUMS) have such a scheme, where 1960, 1970, 1980, and 1990 census occupation and industry codes are mapped to 1950 definitions (variables *occ1950* and *ind1950*). We utilize this uniform occupation classification scheme to merge DOT measures to workers in CPS.[7]

C. Descriptive Analysis

Using the matched data set, Tables 2, 3, and 4 describe the main characteristics of the data. Table 2 reports summary statistics of the variables used in the analysis. On

7. Autor, Levy, and Murnane (2003) have developed their own census occupation code crosswalk over time and have kindly provided it to us. Checks indicate that both crosswalks lead to the same qualitative results. We end up losing a number of observations if we utilize the Autor, Levy, and Murnane (2003) crosswalk, so we use the IPUMS crosswalk.

Table 2
Descriptive Statistics

Variable	Mean	Standard Deviation
Wage income	352.43	(273.44)
Female	0.42	(0.49)
Age	37.50	(12.42)
Experience	19.00	(13.12)
Black	0.09	(0.28)
Other	0.02	(0.15)
In SMSA	0.62	(0.49)
High school graduate	0.59	(0.49)
College +	0.19	(0.39)
Northeast	0.16	(0.37)
Midwest	0.17	(0.38)
South	0.21	(0.41)
West	0.17	(0.38)
Cognitive index	1.01	(0.09)
Motor index	0.99	(0.08)
People index	1.02	(0.09)
Strength	0.28	(0.45)
Number of workers	1,261,184	
Years	1968–90	

Data are from March CPS 1968–90 and DOT (1977, 1991).

average, there are 55,000 workers for each CPS year in our restricted sample as defined above, although the actual number of workers ranges from 43,490 (1975) to 67,882 (1981). On average, 42 percent of the workers in the sample are females, 9 percent are blacks, 62 percent are in statistical metropolitan areas (SMSA), 59 percent have at most a high school degree, and 19 percent have a college degree or more.

Table 3 reports means of DOT skill indices by educational level for selected CPS years. As expected, individuals with higher levels of education are in occupations requiring greater cognitive and people skills, fewer motor skills, and less physical strength. For instance, in 1970, college graduates were in occupations with an average cognitive skill index of 1.09 (equivalent to the cognitive skills of a manager), while high school graduates' jobs required only 0.99 on average (equivalent to the cognitive skills of an office machine operator), followed by 0.94 in jobs occupied by workers without a high school degree (for example, waiters and waitresses). A similar pattern emerges for people skills. In 1970, college graduates were in occupations with an average people skill index of 1.1 (equivalent to the people skills of a teacher), while high school graduates' jobs required only 1.0 on average (equivalent to the people skills of secretaries), followed by 0.96 in jobs occupied by work-

Table 3
Means of Skill Indices by Education Group

	Cognitive Skills					
	1970	1976	1979	1982	1988	1990
Less than high school	0.943	0.940	0.965	0.964	0.966	0.965
High school graduate	0.998	0.993	1.013	1.014	1.015	1.015
College and more	1.090	1.096	1.105	1.104	1.101	1.102
Total	0.992	0.999	1.021	1.023	1.028	1.030
Test: High school = college						
T-statistic	−87.00	−110.00	−120.00	−120.00	−120.00	−130.00
	Motor Skills					
	1970	1976	1979	1982	1988	1990
Less than high school	1.000	1.001	0.995	0.993	0.993	0.992
High school graduate	1.007	1.009	0.991	0.989	0.986	0.985
College and more	0.970	0.967	0.972	0.974	0.974	0.973
Total	1.000	1.000	0.988	0.987	0.984	0.983
Test: high school = college						
T-statistic	28.76	36.77	18.54	15.51	12.53	13.75

	Strength					
	1970	1976	1979	1982	1988	1990
Less than high school	0.459	0.400	0.463	0.464	0.466	0.458
High school graduate	0.269	0.236	0.294	0.289	0.289	0.292
College and more	0.084	0.071	0.158	0.155	0.164	0.155
Total	0.307	0.246	0.304	0.295	0.284	0.281
Test: high school = college						
T-statistic	40.95	43.32	31.47	33.22	32.71	37.45

	People Skills					
	1970	1976	1979	1982	1988	1990
Less than high school	0.962	0.960	0.978	0.978	0.982	0.981
High school graduate	1.000	0.998	1.013	1.014	1.018	1.018
College and more	1.100	1.109	1.102	1.100	1.098	1.098
Total	1.001	1.008	1.022	1.025	1.032	1.033
Test: high school = college						
T-statistic	−77.95	−91.05	−93.12	−96.67	−97.69	−100.00

Data are from March CPS 1968–90 and DOT (1977, 1991).

ers without a high school degree (for example, private household workers). In contrast, physical strength is required in only 8 percent of the occupations of college graduates (for example, teachers are required to have physical strength), while it is required in 27 percent of high school graduates' jobs (for example, operatives), followed by 46 percent of jobs occupied by workers without a high school degree (for example, laborers). It is also worth noting that differences in the various skill requirements across education groups are statistically significant and appear to be stable over time, even within education groups.

Table 4 displays the correlation among the skill requirements of occupations in the 1977 and 1991 DOTs. Occupations that require more cognitive skills tend also to require more people skills over the entire period, suggesting that cognitive and people skills complement each other. Occupations that require fewer people skills tend to require more motor skills and physical strength, and occupations that require more cognitive skills also require less physical strength. Another finding worth pointing out in Table 4 is the increased correlation between cognitive and motor requirements between the 1977 and 1991 DOTs. This cognitive-motor correlation might be due to technical changes and/or computerization in the workplace, particularly since many of the jobs with updated skill requirements are computer-related.

IV. The Returns to Different Skills in the U.S. Economy

A. Specification

In this section, we estimate the wage returns to cognitive, motor, and people skills as well as physical strength in the U.S. labor market between 1968 and 1990. As discussed in Section II, we specify the empirical model as:

$$(3) \quad \ln w_{it} = Z_{it}'\gamma_t + X_{it}'\beta_t + \varepsilon_{it}$$

where w_{it} is the weekly wage earnings of individual i at time t. X_{it} has the standard controls for worker characteristics: the worker's age, age squared, cubic terms for potential work experience, SMSA status, region of residence, and dummies for having a college degree, having a high school degree, gender, race, and marital status. Also, all the regressions include year fixed-effects.

The vector Z_{it} contains the DOT characteristics required to perform the occupation in which individual i is employed and proxies for the worker's cognitive, people, and motor skills as well as physical strength.

The most important econometric issues we face are that worker skills are measured with error and unobserved heterogeneity among workers might be correlated to the skills required by their occupations. Section IVC addresses these issues. An additional concern is that, within an occupation, our DOT skill measures do not vary by worker. Therefore, we face the classic Moulton (1990) problem of estimating the effects of aggregate variables on individual outcomes. We deal with this by clustering the standard errors at the occupation level.

Table 4
Pairwise Correlation Between Skill Requirements

	Cognitive	Motor	Strength	People
1968–77				
Cognitive	1			
Motor	0.06	1		
Strength	−0.42	0.01	1	
People	0.7	−0.4	−0.4	1
1978–91				
	Cognitive	Motor	Strength	People
Cognitive	1			
Motor	0.41	1		
Strength	−0.25	0.14	1	
People	0.83	0.19	−0.24	1

Data are from March CPS 1968–90 and DOT (1977, 1991).

B. Results

The first specification we estimate has cognitive, motor, and people skills as well as physical strength entering separately in the wage equation along with the standard controls. We use the logarithm of our measures of cognitive, motor, and people skills as the regressors so that the estimated parameters are unit-free and can be interpreted as wage elasticities. Our measure of physical strength enters in a linear way since it is a dummy variable.

Table 5 reports the wage returns to these four skills in the U.S. labor market during the 1968–90 period. We report the complete set of parameter estimates and regression statistics in Table A-2 of the online Appendix. The controls for worker characteristics have the expected pattern of sign and significance. Females earn lower wages, while married workers and white workers earn higher wages. Age has an increasing and concave effect on wages. This sign and significance pattern persists in the rest of the paper's wage models, and thus we will not comment further on them.

Cognitive skills were positively and significantly valued in the U.S. labor market throughout the period and became significantly more valuable since the beginning of the 1970s. In this specification, the wage return to cognitive skills increased by about 60 percent between 1968 and 1990. It started rising at the end of the 1960s, stabilized and even declined during the mid-1970s, and then accelerated again at the end of the 1970s and throughout the 1980s. To be concrete, in 1968, a change in

Table 5

Hedonic Price Elasticities of Skill $\left(\frac{\partial ln(w)}{\partial ln(skill)}\right)$

	1968	1969	1970	1971	1972	1973	1974
Cognitive	1.04971	0.9963	1.12545	1.31306	1.3037	1.3243	1.27866
	[0.14279]***	[0.14009]***	[0.14794]***	[0.12254]***	[0.12099]***	[0.12474]***	[0.11868]***
Motor	0.66662	0.62379	0.64281	0.66442	0.67696	0.62574	0.58552
	[0.11099]***	[0.11194]***	[0.12377]***	[0.12266]***	[0.12617]***	[0.12223]***	[0.11146]***
Strength	−0.0644	−0.06008	−0.05166	−0.07612	−0.05852	−0.05561	−0.05826
	[0.02404]***	[0.02267]***	[0.02253]**	[0.02539]***	[0.02559]**	[0.02331]**	[0.02360]**
People	0.31935	0.26748	0.29032	0.3685	0.36378	0.39311	0.40991
	[0.11955]***	[0.11488]**	[0.12847]**	[0.10588]***	[0.10389]***	[0.11361]***	[0.10264]***
	1975	**1976**	**1977**	**1978**	**1979**	**1980**	**1981**
Cognitive	1.3118	1.17723	1.24577	1.09607	1.13452	1.21402	1.22916
	[0.11935]***	[0.12168]***	[0.12208]***	[0.14572]***	[0.13661]***	[0.12999]***	[0.13362]***
Motor	0.54914	0.66686	0.64314	0.59349	0.5392	0.5212	0.59211
	[0.11428]***	[0.12572]***	[0.12014]***	[0.12025]***	[0.11858]***	[0.11575]***	[0.11240]***
Strength	−0.06268	−0.04391	−0.0339	0.01864	0.01911	0.01193	0.01766
	[0.02360]***	[0.02609]*	[0.02478]	[0.02124]	[0.02106]	[0.02153]	[0.02203]
People	0.3996	0.27353	0.28417	0.28671	0.29153	0.39691	0.29224
	[0.10237]***	[0.10461]***	[0.10219]***	[0.11183]**	[0.11790]**	[0.11475]	[0.11640]

	1982	1983	1984	1985	1986
Cognitive	1.27187	1.27917	1.40325	1.44696	1.4223
	[0.14436]***	[0.14355]***	[0.13238]***	[0.14805]***	[0.13852]***
Motor	0.62253	0.62674	0.53119	0.49433	0.49222
	[0.12271]***	[0.12595]***	[0.11995]***	[0.12725]***	[0.12603]***
Strength	0.01965	0.02175	0.00461	−0.00032	−0.00779
	[0.02390]	[0.02497]	[0.02244]	[0.02192]	[0.02269]
People	0.32094	0.30856	0.40892	0.46973	0.43344
	[0.12415]***	[0.13747]**	[0.12808]***	[0.13968]***	[0.14133]***

	1987	1988	1989	1990
Cognitive	1.49852	1.56656	1.5988	1.61695
	[0.13605]***	[0.14012]***	[0.14171]***	[0.14137]***
Motor	0.49747	0.47825	0.42578	0.41138
	[0.13047]***	[0.13073]***	[0.12743]***	[0.12706]***
Strength	−0.00535	−0.00826	−0.00183	−0.00153
	[0.02175]	[0.02164]	[0.02214]	[0.02168]
People	0.5293	0.52727	0.58707	0.60069
	[0.14151]***	[0.14930]***	[0.14806]***	[0.14241]***

Note: Each cell constitutes a separate regression. Robust standard errors in brackets, clustered at occupation and industry level. * denotes significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent. All regressions include controls for age, age squared, experience, experience squared, experience cubed, indicators for female, black, other nonwhite race, marital status, SMSA status, high school graduate, college graduate, region dummies, and a constant. Estimates of other regression coefficients are reported in Table A-2 of the online Appendices.

occupation associated with a one standard deviation increase in cognitive skill requirements, such as going from having the cognitive skills required to be a carpenter or car mechanic to having the cognitive skills required to be a draftsperson or designer, was associated with a 10.5 percent increase in wages. By 1975, the same occupational change was associated with a 13.1 percent higher wage. Such a skill premium declined to 10.9 percent by 1978 and then steadily increased. By 1990, the same one standard deviation change in skill requirements was associated with a 16.2 percent increase in wages.

Motor skills were also positively and significantly valued throughout the period. As opposed to cognitive skills, motor skills became significantly less valuable over time, with the wage return to motor skills decreasing by more than 50 percent between 1968 and 1990. During the 1970s, the wage return to motor skills fluctuated without a clear trend. Since 1983, the return to these skills declined steadily, at an annual rate of 3 percent. In 1968, a change in occupation implying a one standard deviation increase in motor skill requirements, equivalent to going from having the motor skills of an economist or a psychologist to having the motor skills of a metallurgical engineer, was associated with a 6.6 percent rise in wages. The value of motor skills fell in the 1980s, and by 1990 the same occupational change was associated with only a 4.1 percent wage differential.

People skills were also positively and significantly valued in the U.S. labor market throughout the period. The wage return to people skills doubled between 1968 and 1990, the largest price increase of any of the four skills during the period. Like the return to motor skills, the return to people skills fluctuated without a trend until 1983 and then increased steadily until 1990. Between 1983 and 1990, the return to people skills increased at an annual rate of 4 percent. In 1968, a change in occupation that implied a one standard deviation increase in people skill requirements, equivalent to going from having the people skills of laborers, carpenters, or bookkeepers to having the people skills of sports officials, public administrators, or librarians, was associated with a 3.2 percent rise in wages. The value of people skills increased in the 1980s, and by 1990 the same occupational change was associated with a 6.0 percent increase in wages.

Finally, the wage return to being in occupations that required physical strength was negative and small in the late 1960s and 1970s and zero by the 1980s.

As a robustness check, Table 6 reports the wage returns to each of the DOT skill measures used to construct the cognitive, motor, and people indices.[8] Interestingly, all the different aspects of cognition were valuable in the U.S. labor market and became more valuable in the 1980s. Five of the nine DOT measures used to construct the motor index were also significantly valued in the U.S. labor market, with all the measures either not changing in value or becoming less valuable in the 1980s. The four variables used to construct the people index also became more valuable in the 1980s, with two having statistically positive wage returns. This confirms that the patterns uncovered by our analysis using the skill indices are very much present in the underlying skill data.

8. To conserve space, we report the results for the 1980s only since, as discussed in the previous paragraphs, most of the estimated changes in skill prices happened then.

Table 6
Robustness: Returns to Individual Skill

	1980	1981	1982	1983	1984	1985
Cognitive index components						
Data	0.05381	0.05371	0.05476	0.0558	0.06113	0.0658
	[0.00609]***	[0.00639]***	[0.00688]***	[0.00708]***	[0.00673]***	[0.00706]***
gedr	0.10435	0.10682	0.1113	0.1109	0.11931	0.12188
	[0.01135]***	[0.01177]***	[0.01295]***	[0.01293]***	[0.01157]***	[0.01270]***
gedm	0.09587	0.09683	0.10185	0.10279	0.10788	0.11201
	[0.00942]***	[0.00963]***	[0.01014]***	[0.01015]***	[0.00969]***	[0.01080]***
gedl	0.07737	0.07664	0.07982	0.08122	0.09126	0.09334
	[0.00991]***	[0.01028]***	[0.01109]***	[0.01166]***	[0.01027]***	[0.01136]***
aptg	0.15265	0.15161	0.1562	0.15717	0.17449	0.17965
	[0.01791]***	[0.01807]***	[0.01989]***	[0.02063]***	[0.01838]***	[0.02082]***
aptv	0.10881	0.10621	0.11076	0.11103	0.12819	0.1293
	[0.01620]***	[0.01617]***	[0.01765]***	[0.01822]***	[0.01634]***	[0.01829]***
aptn	0.13207	0.13933	0.14007	0.1409	0.15334	0.15519
	[0.01458]***	[0.01450]***	[0.01590]***	[0.01557]***	[0.01527]***	[0.01671]***
Motor index components						
Things	0.0195	0.02239	0.023	0.02194	0.01917	0.01718
	[0.00519]***	[0.00526]***	[0.00594]***	[0.00628]***	[0.00577]***	[0.00601]***
aptf	0.06132	0.07548	0.07833	0.08568	0.06886	0.07025
	[0.02086]***	[0.01959]***	[0.02147]***	[0.02175]***	[0.01986]***	[0.02028]***

(continued)

Table 6 *(continued)*

aptk	0.01343	0.01764	0.02774	0.02524	0.00829	0.01121
	[0.02340]	[0.02256]	[0.02363]	[0.02472]	[0.02444]	[0.02517]
aptm	-0.00829	−0.00597	−0.00215	0.01296	−0.01524	−0.02327
	[0.02103]	[0.01992]	[0.02289]	[0.02458]	[0.02255]	[0.02368]
apte	0.00974	0.00793	0.02022	0.0175	−0.00167	−0.00425
	[0.01887]	[0.01927]	[0.02013]	[0.02063]	[0.01966]	[0.01929]
apts	0.13832	0.14302	0.15312	0.1519	0.13827	0.13287
	[0.01400]***	[0.01463]***	[0.01525]***	[0.01593]***	[0.01517]***	[0.01637]***
aptp	0.11647	0.12728	0.12977	0.12489	0.12776	0.11964
	[0.01874]***	[0.01914]***	[0.02045]***	[0.02129]***	[0.02000]***	[0.02101]***
aptc	-0.00055	−0.00352	0.00089	0.00772	0.00273	−0.00061
	[0.01820]	[0.01885]	[0.02004]	[0.02143]	[0.02021]	[0.02034]
sts	0.0746	0.10627	0.09932	0.09121	0.08045	0.06799
	[0.02909]**	[0.02910]***	[0.03113]***	[0.03073]***	[0.03012]***	[0.03167]**
People index components						
depl	-0.01719	−0.03909	−0.03599	−0.03386	−0.01831	−0.0073
	[0.02478]	[0.02450]	[0.02686]	[0.02611]	[0.02523]	[0.02664]
dcp	0.18675	0.16673	0.17861	0.18214	0.1928	0.20729
	[0.02646]***	[0.02763]***	[0.02976]***	[0.03099]***	[0.02752]***	[0.02838]***
influ	-0.05346	−0.06317	−0.06735	−0.08095	−0.05784	−0.07
	[0.04503]	[0.04713]	[0.04537]	[0.04264]*	[0.04100]	[0.04210]*
peovar	0.02658	0.02245	0.02285	0.02178	0.02619	0.0275
	[0.00658]***	[0.00665]***	[0.00728]***	[0.00826]***	[0.00722]***	[0.00800]***

	1986	1987	1988	1989	1990
Cognitive index components					
data	0.06366	0.06658	0.07123	0.07254	0.07447
	[0.00670]***	[0.00659]***	[0.00673]***	[0.00693]***	[0.00659]***
gedr	0.11994	0.12678	0.13266	0.13582	0.1371
	[0.01212]***	[0.01231]***	[0.01251]***	[0.01256]***	[0.01234]***
gedm	0.11247	0.11541	0.12033	0.1227	0.12202
	[0.00988]***	[0.00980]***	[0.01009]***	[0.01039]***	[0.01066]***
gedl	0.09186	0.0967	0.10013	0.10394	0.10338
	[0.01106]***	[0.01110]***	[0.01140]***	[0.01134]***	[0.01130]***
aptg	0.17493	0.18322	0.19177	0.19162	0.19725
	[0.01983]***	[0.01967]***	[0.02048]***	[0.02050]***	[0.02037]***
aptv	0.1257	0.13553	0.14181	0.14096	0.14901
	[0.01766]***	[0.01788]***	[0.01848]***	[0.01845]***	[0.01823]***
aptn	0.15548	0.16376	0.16983	0.17686	0.1739
	[0.01576]***	[0.01517]***	[0.01556]***	[0.01635]***	[0.01655]***
Motor index components					
Things	0.01613	0.01728	0.0178	0.01438	0.01322
	[0.00597]***	[0.00597]***	[0.00617]***	[0.00585]**	[0.00609]**
aptf	0.06911	0.07103	0.06813	0.06027	0.05555
	[0.02098]***	[0.02211]***	[0.02187]***	[0.02109]***	[0.02091]***
aptk	-0.00069	0.00213	−0.00609	−0.0131	−0.01382
	[0.02527]	[0.02498]	[0.02581]	[0.02497]	[0.02509]
aptm	-0.01968	−0.01413	−0.02647	−0.02953	−0.03597
	[0.02410]	[0.02514]	[0.02488]	[0.02370]	[0.02497]

(continued)

Table 6 *(continued)*

apte	-0.01201	0.0004	−0.00957	−0.00542	−0.00675
	[0.01956]	[0.01986]	[0.02061]	[0.02132]	[0.02058]
apts	0.13656	0.1402	0.1385	0.13873	0.13967
	[0.01601]***	[0.01692]***	[0.01675]***	[0.01771]***	[0.01668]***
aptp	0.12577	0.12526	0.12566	0.12069	0.11882
	[0.02043]***	[0.02103]***	[0.02114]***	[0.02160]***	[0.02012]***
aptc	0.0118	0.01168	0.0105	0.00436	0.01077
	[0.02062]	[0.02099]	[0.02094]	[0.02113]	[0.02113]
sts	0.07265	0.04636	0.05718	0.04739	0.04061
	[0.03238]**	[0.03095]	[0.03210]*	[0.03111]	[0.03282]
People index components					
depl	-0.00754	0.01274	0.0048	0.02084	0.02414
	[0.02566]	[0.02563]	[0.02674]	[0.02604]	[0.02625]
dcp	0.18785	0.20484	0.2077	0.20808	0.22412
	[0.02977]***	[0.02868]***	[0.03042]***	[0.02956]***	[0.02892]***
influ	-0.05659	−0.05117	−0.04215	−0.02636	−0.04284
	[0.04269]	[0.04444]	[0.04485]	[0.04399]	[0.04434]
peovar	0.02502	0.02887	0.02937	0.03122	0.03113
	[0.00824]***	[0.00861]***	[0.00889]***	[0.00878]***	[0.00828]***

Note: Robust standard errors in brackets, clustered at occupation and industry level. * denotes significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent. All regressions include controls for age, age squared, experience, experience squared, experience cubed, indicators for female, black, other nonwhite race, marital status, SMSA status, high school graduate, college graduate, region dummies, and a constant.

To summarize the results so far, cognitive, motor, and people skills were valued in the U.S. labor market in the 1970s and 1980s. However, while cognitive and people skills increased in value over time, motor skills became less valuable in the 1968–90 period.

The wage models with skills entering individually are both simple and transparent. However, they do not examine the possibility of complementarity among skills. For instance, the return to cognitive skills could differ in occupations that require many or few people skills (for example, a therapist compared to a meat cutter). Indeed, the skill correlations in Table 4 suggest that skills may interact in the performance of job-specific tasks. To allow for these complementarities among skills, we estimate our wage equation with interaction terms among DOT skill measures.[9]

Table 7 reports the wage returns of skills when we estimate Equation 1, with the skill vector Z_{it} containing interactions among the four skills discussed above. Before discussing the results, it is worth noting that, in Table 7, the coefficient on the linear term of each skill is also the total wage return of this skill evaluated at the mean value of cognitive, motor, and people skills for occupations that do not require physical strength. This is the case because, by construction, the cognitive, motor, and people skill indices have mean 1 in the population. Therefore, at the population mean $\ln(Z_{it}) = 0$ and the interaction terms drop out.

Cognitive skills continued to be significantly valued in the U.S. labor market throughout the period. Once we allow for complementarities among skills, the wage return of cognitive skills more than doubled between 1968 and 1990. Half of the wage return of cognitive skills increase occurred in the first few years of the 1970s. In the remaining years of the 1970s, the return to cognitive skills stayed constant before steadily increasing throughout the 1980s.

The interaction terms highlight an interesting pattern of complementarities. Cognitive skills are more valuable in occupations that require less motor skills, no physical strength, and more people skills. In addition, over time, cognitive skills have become more complementary to motor and especially people skills.

Motor skills also continue to have been significantly valued in the U.S. labor market once we allow for skill complementarities. In this case, the wage return to motor skills decreased by more than previously estimated. Between 1968 and 1990, the price of motor skills declined by about 60 percent. As before, virtually all of this decline occurred in the 1980s.

The interaction terms reveal that motor skills were complementary to physical strength in the 1970s but not in the 1980s. Meanwhile people skills become complementary to motor skills in the mid 1970s, and this complementarity increased over time.

The wage return to people skills varied significantly across the distribution of the other DOT skills. Evaluated at the mean values of cognitive and motor skills and for occupations that do not require physical strength, the wage return to people skills was negative or zero. This is what the coefficient on measures. However, the interaction terms show that people skills complement all the other skills. For instance, for occupations that required physical strength ($strength = 1$), the wage return to

9. We also added quadratic terms, which were not statistically significant.

Table 7

Hedonic Price Elasticities of Skill $\left(\frac{\partial ln(w)}{\partial ln(skill)}\right)$ *from Model with Skill Interactions*

	1968	1969	1970	1971	1972	1973	1974
Cognitive	0.93179	0.97374	1.14518	1.47199	1.45422	1.5293	1.45867
	[0.18228]***	[0.18816]***	[0.20934]***	[0.16568]***	[0.16939]***	[0.16512]***	[0.16436]***
Motor	0.65246	0.58269	0.51838	0.50008	0.45145	0.42106	0.4233
	[0.20391]***	[0.20584]***	[0.22631]**	[0.20799]**	[0.21952]**	[0.19547]**	[0.18110]**
Strength	−0.03486	−0.02843	−0.01026	−0.03384	−0.01534	−0.01524	−0.0075
	[0.04494]	[0.03691]	[0.03555]	[0.04237]	[0.03975]	[0.03362]	[0.03261]
People	−0.04429	−0.17996	−0.22691	−0.36819	−0.36461	−0.3182	−0.32809
	[0.16031]	[0.17247]	[0.19438]	[0.18396]**	[0.18375]**	[0.18279]*	[0.17978]*
Cognitive*motor	−4.86366	−5.9211	−6.16883	−5.3797	−4.8355	−5.35698	−5.30307
	[1.92244]**	[1.96608]***	[2.13714]***	[1.99439]***	[2.07610]**	[1.86413]***	[1.72551]***
Cognitive*strength	−0.75834	−0.96068	−0.85884	−1.29236	−1.41318	−1.12457	−0.96439
	[0.65364]	[0.56091]*	[0.54574]	[0.56211]**	[0.54537]***	[0.46361]**	[0.47188]**
Cognitive*people	1.32466	0.96805	0.41758	2.7831	2.75077	2.15766	3.23161
	[2.73956]	[2.67707]	[2.93988]	[1.99100]	[2.02332]	[2.26544]	[1.82505]*
Motor*strength	0.56078	0.67466	0.76291	1.01383	1.3172	0.97891	0.85064
	[0.51633]	[0.48082]	[0.47442]	[0.43925]**	[0.45436]***	[0.40068]**	[0.38971]**
Motor*people	0.75699	1.77303	1.58216	1.85456	1.75452	2.92427	2.97201
	[1.72063]	[1.74292]	[1.93992]	[1.47477]	[1.48835]	[1.55411]*	[1.34257]**
Strength*people	0.30717	0.69067	0.55608	0.91927	1.14488	0.66541	0.74147
	[0.45011]	[0.43827]	[0.43287]	[0.41029]**	[0.44777]**	[0.41454]	[0.41563]*

	1975	1976	1977	1978	1979	1980	1981
Cognitive	1.50155	1.39247	1.5224	1.46363	1.56468	1.50482	1.60779
	[0.16183]***	[0.17148]***	[0.16443]***	[0.19841]***	[0.17754]***	[0.18418]***	[0.18837]***
Motor	0.2642	0.42203	0.39239	0.60444	0.51506	0.55026	0.57325
	[0.18405]	[0.21085]**	[0.19697]**	[0.19889]***	[0.20261]**	[0.18838]***	[0.19342]***
Strength	−0.01454	−0.00364	0.02063	0.04036	0.04792	0.04954	0.05329
	[0.03261]	[0.03614]	[0.03161]	[0.02260]*	[0.02270]**	[0.02410]**	[0.02351]**
People	−0.39454	−0.40406	−0.48106	−0.41375	−0.44587	−0.42819	−0.54428
	[0.18348]**	[0.19393]**	[0.18105]***	[0.22014]*	[0.21291]**	[0.20584]**	[0.20849]***
Cognitive*motor	−3.67122	−3.50034	−5.2873	−4.10764	−3.86847	−3.79207	−3.75733
	[1.75910]**	[1.99920]*	[1.88395]***	[1.65564]**	[1.68299]**	[1.57861]**	[1.62718]**
Cognitive*strength	−0.89914	−0.81213	−0.77116	−0.94224	−0.93369	−0.14077	−0.37346
	[0.45103]**	[0.48584]*	[0.44468]*	[0.50799]*	[0.44337]**	[0.47962]	[0.44720]
Cognitive*people	3.0501	3.84004	3.32002	4.80141	3.98398	5.62759	4.89358
	[1.94566]	[1.89329]**	[1.74491]*	[2.01270]**	[2.04162]*	[1.85725]***	[1.85427]***
Motor*strength	1.19251	1.05195	0.97774	0.45615	0.48239	−0.03429	0.16357
	[0.38553]***	[0.43998]**	[0.40427]**	[0.43192]	[0.41081]	[0.43253]	[0.41625]
Motor*people	2.04204	2.12905	2.84882	3.12256	2.76211	2.90183	2.42379
	[1.47744]	[1.44564]	[1.35112]**	[1.42794]**	[1.47445]*	[1.31154]**	[1.34000]*
Strength*people	0.61646	0.50172	0.57541	0.39399	0.36001	−0.17451	0.04399
	[0.42784]	[0.44313]	[0.40910]	[0.72407]	[0.68753]	[0.76430]	[0.70526]

(continued)

Table 7 *(continued)*

	1982	1983	1984	1985	1986
Cognitive	1.69221	1.70187	1.79585	1.79933	1.78099
	[0.19085]***	[0.19898]***	[0.18846]***	[0.20598]***	[0.19500]***
Motor	0.59206	0.51221	0.4246	0.46113	0.41178
	[0.20371]***	[0.21073]**	[0.20454]**	[0.21591]**	[0.21462]*
Strength	0.05376	0.06421	0.05079	0.04933	0.04271
	[0.02538]**	[0.02647]**	[0.02351]**	[0.02301]**	[0.02373]*
People	−0.52513	−0.51532	−0.63134	−0.58133	−0.57977
	[0.22558]**	[0.22183]**	[0.20534]***	[0.21224]***	[0.21765]***
Cognitive*motor	−4.41484	−3.16705	−3.54199	−3.73309	−3.61892
	[1.62185]***	[1.64545]*	[1.48056]**	[1.62859]**	[1.56634]**
Cognitive*Strength	−0.77857	−0.11618	−0.35212	−0.16194	−0.04768
	[0.47058]*	[0.51977]	[0.48303]	[0.44961]	[0.46243]
Cognitive*People	4.42031	4.26206	5.22458	4.85633	3.87616
	[2.04899]**	[2.19477]*	[1.84391]***	[2.02275]**	[2.11852]*
Motor*strength	0.22283	−0.18945	0.10002	−0.1614	−0.17062
	[0.42657]	[0.49946]	[0.45740]	[0.44253]	[0.45352]
Motor*people	3.54783	3.07203	2.89202	2.67433	2.67491
	[1.39001]**	[1.46221]**	[1.34119]**	[1.41574]*	[1.44014]*
Strength*people	0.39643	−0.29934	0.19096	0.02384	−0.10462
	[0.74796]	[0.85159]	[0.72229]	[0.69145]	[0.71196]

	1987	1988	1989	1990
Cognitive	1.81464	1.92295	1.89812	1.97939
	[0.18202]***	[0.19912]***	[0.19818]***	[0.19921]***
Motor	0.3539	0.42424	0.38155	0.26317
	[0.18920]*	[0.20847]**	[0.19860]*	[0.20014]
Strength	0.05226	0.04772	0.05735	0.06607
	[0.02328]**	[0.02271]**	[0.02346]**	[0.02290]***
People	−0.45139	−0.54865	−0.52618	−0.5014
	[0.21491]**	[0.22467]**	[0.22963]**	[0.23124]**
Cognitive*motor	−2.44065	−4.16616	−3.28613	−3.31446
	[1.47672]*	[1.52589]***	[1.48597]**	[1.49963]**
Cognitive*strength	0.00858	−0.03472	−0.12798	0.04491
	[0.48404]	[0.48634]	[0.53279]	[0.51712]
Cognitive*people	3.42452	3.23149	3.34902	3.10818
	[2.12615]	[2.13560]	[2.17964]	[2.08164]
Motor*strength	−0.14126	−0.23283	−0.04651	−0.07293
	[0.43399]	[0.45671]	[0.48536]	[0.48973]
Motor*people	2.95463	3.09731	1.70023	3.11546
	[1.50318]**	[1.61544]*	[1.60208]	[1.59463]*
Strength*people	−0.05743	−0.06568	0.18031	−0.12444
	[0.70634]	[0.69921]	[0.74965]	[0.81099]

Note: Robust standard errors in brackets, clustered at occupation and industry level. * denotes significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent. All regressions include controls for age, age squared, experience, experience squared, experience cubed, indicators for female, black, other nonwhite race, marital status, SMSA status, high school graduate, college graduate, region dummies, and a constant.

people skills became positive, even at the mean values of cognitive and motor skills. The same is true for occupations requiring above average cognitive and/or motor skills. For these occupations, people skills were positively and significantly valued. These findings show that people skills were not valued by themselves in the U.S. labor market but that they raised the returns to cognitive and motor skills and even physical strength (in some years of the sample period). Moreover, the complementarity of people skills with cognitive and motor skills strongly increased over time, which is why people skills became more valuable during the 1968–90 period.

Finally, the wage return to being in occupations that require above average physical strength was zero in the 1970s and positive but quite small in the 1980s. As discussed above, physical strength was complementary to motor skills in the 1970s but not in the 1980s and tended to be more valuable with people skills and less valuable with cognitive skills.

To summarize, the 1970s and 1980s witnessed a large increase in the wage returns to cognitive and people skills, with the distinction that people skills became more valuable by being complementary to other skills. There was also a large decline in the wage return to motor skills during these decades. Physical strength became somewhat more valuable in the 1980s but not significantly so.

C. Robustness: Mismeasured Skills, Unobserved Characteristics, and Workers Selection

We turn now to the robustness of the estimates obtained in the previous section. There are a number of possible reasons why our data on workers' skills might be measured with error. For instance, the skill requirements of occupations may vary within the three-digit occupational categories we use. If such variation is systematically correlated with the measured DOT requirements, our parameter estimates will be biased. Also, the DOT codebook characterizes occupation skill requirements as minimums. It is possible, therefore, that workers have skills that exceed the DOT requirements for their jobs. In this case, we would underestimate worker skills. Irrespective of the source of mismeasurement, if errors are unrelated to the measured skill requirements of occupations, no bias would be introduced into the estimation, although the estimation would become less precise. Also, if workers are not compensated for skills in excess of the occupation's requirements, no bias would be introduced. Our estimates would be biased if any excess skills are both rewarded and also somehow correlated with the measured skill requirements. It is worth noting that if the skill space is compact and all skills have a positive hedonic price, then there would be no possibility of workers having more skills than the occupation requirements. This compactness assumption is obviously never met exactly but may be close to correct given the large number of occupations we have in the data.

In a similar way, our estimates would also be biased if workers have unobserved characteristics that are correlated with their measured DOT skills. We deal with these possibilities by utilizing the NLSY79 data set. The NLSY79 data set contains additional individual-level measures of skills, such as AFQT scores, that are not available in CPS. It also allows us to estimate individual fixed effects models to capture the impact of time-invariant unobserved ability on wages since it follows individuals over time.

Table A-3 in the online Appendix provides summary statistics of the NLSY79 sample. We estimate the wage returns to cognitive, motor, and people skills as well as physical strength for the period 1978–90 (survey years 1979–91). In the first specification, we stack all years and control for individual skills (for example, AFQT score) and family background but do not utilize the data's panel structure. In the second specification, we control for individual fixed-effects. The fixed-effects specification controls for any observed or unobserved individual characteristic that affects a worker's wage as long as this characteristics is time invariant.

Table 8 shows the estimated wage returns of skills in the NLSY79 sample. The first columns have the estimates controlling for individual skills and family background. The second set of columns has the estimates of the model with individual fixed-effects. In both specifications, we interact skill requirements with a linear trend to capture the evolution of skill returns over time. We also estimate a specification where skill requirements are interacted with year dummies, and the same qualitative results hold.

Both specifications confirm that the price of cognitive and people skills increased while the price of motor skills declined between 1979 and 1991. As expected, the specification with individual fixed-effects shows less pronounced changes in the wage returns to skills. The specifications with all the variables and their interactions show the same pattern of results as before, except that the significance levels are lower. This should be expected given the smaller sample size and the stronger demands that the individual fixed effects specification imposes on the data.

In summary, to the extent that data mismeasurements and/or unobserved skills are uncorrelated with the measured skills, our skill price estimates are unbiased. If they are correlated with the measured skills but are time-invariant, we can control for them using the panel structure of NLSY79. When we do so, we confirm the main patterns found in the CPS data.

It is possible, however, that the unobserved characteristics of workers are changing over time in ways that are systematically related to their cognitive, motor, and people skills as well as their physical strength. The most likely reason why this could happen is that the underlying quality of workers in the labor force can change in ways that cannot be captured with our data. This is particularly important for women, a group that has seen a large increase in its labor force participation rates. Thus, our wage return estimates might be spuriously picking up changes in the unobserved quality of workers in the labor force.[10]

We check for this possibility by controlling for the labor force participation decision of women using a Heckman selection model. To estimate this model, we use the number of children under the age of six and marital status as exclusion restrictions, which Mulligan and Rubinstein (2004, 2005) discuss in detail.

Table A-5 in the online Appendix shows the estimated wage returns to skills in this case. These do not differ qualitatively from the estimates without controlling for selection in terms of significances and magnitudes and, more importantly for our

10. For instance, Mulligan and Rubinstein (2004, 2005) argue that, for married white women at peak earning ages working full time full year, quality changes account for all of the narrowing of the gender gap.

Table 8

Hedonic Price Elasticities of Skill $\left(\frac{\partial ln(w)}{\partial ln(skill)}\right)$ *With Individual Fixed Effects, NLSY79*

	Stacked OLS				
	Cognitive	Motor	Strength	People	All
Cognitive	0.13372				0.94471
	[0.19038]				[0.28642]***
Motor		1.15862			0.50542
		[0.20719]***			[0.25427]**
Strength			0.10838		0.04676
			[0.03795]***		[0.03158]
People				−1.06844	−1.36013
				[0.29412]***	[0.57010]**
Cognitive*motor					−6.00201
					[2.59904]**
Cognitive*strength					−0.19515
					[0.66623]
Cognitive*people					5.07183
					[3.25023]
Motor*strength					0.00853
					[0.43875]
Motor*people					7.87063
					[3.73302]**
Strength*people					−0.13928
					[0.69738]

Trend	−0.00357	0.00245	0.00942	−0.00103	−0.00399
	[0.00239]	[0.00259]	[0.00307]***	[0.00243]	[0.00350]
Trend interacted with					
Cognitive	0.13045				0.13104
	[0.01584]***				[0.03388]***
Motor		−0.07177			−0.01205
		[0.02078]***			[0.03041]
Strength			−0.01396		0.00045
			[0.00438]***		[0.00413]
People				0.14412	−0.00154
				[0.02190]***	[0.05607]
Cognitive*motor					−0.1711
					[0.24200]
Cognitive*strength					−0.10146
					[0.06771]
Cognitive*people					0.01997
					[0.31414]
Motor*strength					0.02441
					[0.04022]
Motor*people					−0.10083
					[0.28611]
Strength*people					0.09562
					[0.05996]
Constant	0.02857	−0.07345	−0.03941	−0.0761	0.01717
	[0.09729]	[0.10434]	[0.14907]	[0.10097]	[0.10453]
Observations	89,071	89,071	90,617	89,071	89,071
Number of persons	10,959	10,959	10,959	10,959	10,959
R-squared	0.22	0.21	0.21	0.21	0.24

(continued)

Table 8 *(continued)*

	Fixed Effects				
	Cognitive	Motor	Strength	People	All
Cognitive					
Motor					
Strength					
People					
Cognitive*motor					
Cognitive*strength					
Cognitive*people					
Motor*strength					
Motor*people					
Strength*people					
Trend	0.17888 [0.26233]	0.16794 [0.26039]	0.20412 [0.24556]	0.18136 [0.25970]	0.15898 [0.26279]

Trend interacted with					
Cognitive	0.09931				0.14968
	[0.01056]***				[0.02158]***
Motor		−0.02785			−0.01634
		[0.01052]***			[0.02103]
Strength			−0.00551		0.00584
			[0.00181]***		[0.00223]***
People				0.08077	−0.01333
				[0.01189]***	[0.03320]
Cognitive*motor					−0.06271
					[0.17808]
Cognitive*strength					−0.08262
					[0.03971]**
Cognitive*people					−0.12842
					[0.20481]
Motor*strength					−0.00281
					[0.02803]
Motor*people					−0.05701
					[0.19600]
Strength*people					0.02288
					[0.03926]
Constant	4.06583	4.07916	4.49599	4.17619	3.69965
	[4.51693]	[4.48417]	[4.23081]	[4.47217]	[4.52494]
Observations	89,071	89,071	90,617	89,071	89,071
Number of persons	10,959	10,959	10,959	10,959	10,959
R-squared	0.5	0.5	0.5	0.5	0.51

Note: * denotes significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent. The dependent variable is log real hourly wages. Robust standard errors in brackets, clustered at occupation*year. Other controls are age, quadratic terms for highest grade completed, dummies for education completed (elementary, high school, or college), marital status, region of residence, whether or not the residence is in an SMSA, dummies for missing, and a constant. In addition, the OLS columns control for the following time-invariant characteristics: dummies for gender, black, other nonwhite race, and whether foreign-born; AFQT score, father and mother's highest grades completed, whether or not lived with mom at age 14, and dummies for missing.

purposes, in how these estimates change over time. Note also that the timing of the price changes do not vary across models that do or do not control for selection. As an additional check, we estimate our wage models on subsamples containing men and white men only, groups with relatively stable and strong labor force attachment and thus less subject to changing selection issues. Tables A-6 and A-7 in the online Appendix show the results. The main pattern of results holds in these subsamples as well. The price of cognitive skills increases substantially throughout the period and the price of motor skills declines starting in 1983. People skills have not become more valuable by themselves but the coefficients of the interaction terms are larger in the 1980s, especially the interaction with cognitive skills. One difference is that the coefficient on motor skills is not statistically different than zero in the first half of the 1970s.

In summary, while changes in the way workers (women in particular) sort themselves into the labor force may induce a time-varying correlation between workers' unobserved characteristics and their observed skills, our evidence shows that the main patterns in our estimates are not sensitive to changing potential selection bias. We continue to find a strong increase in the price of cognitive and people skills and a decline in the price of motor skills.

V. Returns to Skills and Residual Inequality

Could the estimated changes in wage returns to skills explain the rise in residual inequality observed in the U.S. labor market? Table 9 shows the cognitive-to-motor skills intensity of workers by percentile of the wage distribution for each education group. Data on the people-to-motor skills intensity show similar patterns and are not reported to conserve space. Throughout the period, among high school and college graduates, the top of the wage distribution was comprised of occupations relatively intensive in cognitive and people skills. On the other side, concentrated at the bottom of the wage distribution, were occupations intensive in motor skills. Therefore, the estimated increase in wage returns to cognitive and people skills and decline in wage return to motor skills should be expected to have raised within-education group inequality for high school and college graduates but not for workers with less than a high school degree.

The first column in Table 10 shows the actual change in the ratio of the 90th to 10th percentile of the wage distribution. It summarizes the patterns of residual inequality for the entire sample and for different education groups and confirms the general patterns found in the literature (see Katz and Autor 1999 for a survey). Important for our purposes is that it shows that residual inequality changed differently for different education groups and in different time periods. Consistent with our story, residual inequality grew considerably less among workers with less than a high school degree and during the second half of the 1970s. As discussed, the prices of cognitive and people skills relative to motor skills increased in the early 1970s and again in the 1980s but not in the second half of the 1970s. Also, it was among high school and college graduates that the top of the wage distribution was strongly skewed toward cognitive- and people-intensive occupations.

Table 9
Cognitive to Motor Intensity by Education Group and Residual Wage Percentile

	Adjusted Wage Distribution Percentile			
1970	10th	25th	75th	90th
Less than high school	0.96	0.952	0.94	0.946
	(0.074)	(0.077)	(0.085)	(0.092)
High school graduate	0.984	0.981	1.005	1.024
	(0.09)	(0.096)	(0.118)	(0.124)
College +	1.105	1.109	1.132	1.142
	(0.153)	(0.14)	(0.112)	(0.111)
Total	0.997	0.993	1.008	1.022
	(0.11)	(0.113)	(0.125)	(0.13)
1980	10th	25th	75th	90th
Less than high school	0.985	0.976	0.968	0.971
	(0.081)	(0.078)	(0.086)	(0.085)
High school graduate	1.018	1.015	1.035	1.05
	(0.101)	(0.104)	(0.116)	(0.12)
College +	1.115	1.115	1.14	1.139
	(0.14)	(0.135)	(0.12)	(0.13)
Total	1.036	1.034	1.05	1.06
	(0.118)	(0.119)	(0.126)	(0.129)
1990	10th	25th	75th	90th
Less than high school	0.985	0.979	0.979	0.98
	(0.089)	(0.084)	(0.094)	(0.096)
High school graduate	1.027	1.025	1.051	1.061
	(0.103)	(0.105)	(0.113)	(0.114)
College +	1.103	1.109	1.15	1.155
	(0.132)	(0.131)	(0.115)	(0.126)
Total	1.042	1.042	1.069	1.076
	(0.116)	(0.118)	(0.124)	(0.127)

Note: Above wage percentiles are determined from residuals of separate regressions, by education group and year, of log wages on age, age squared, experience, experience squared, experience cubed, indicators for female, black, other nonwhite race, marital status, SMSA status, region dummies, and a constant. Two-tailed *t*-tests (not reported) show the means reported above are statistically different across residual wage percentiles at the 1 percent level, except for the “less than high school” category.

Table 10
Components of Changes in Residual Inequality (Ratio of the 90th to 10th Percentile of the Wage Distribution)

Period	Total Change	Observed Quantities (X,Z)	Prices of Observed Quantities Except DOT Skills (β)	Prices of DOT Skills (γ)	Unobserved Prices and Quantities
All sample					
1969–89	0.1778	0.0325	−0.0207	0.0450	0.1210
1969–75	0.0576	0.0269	−0.0070	0.0211	0.0166
1975–80	−0.0362	−0.0070	−0.0424	0.0032	0.0101
1980–89	0.1564	0.0127	0.0287	0.0207	0.0943
Less than high school					
1969–89	0.0993	0.0117	−0.0652	0.0171	0.1357
1969–75	0.0445	0.0059	−0.0205	0.0065	0.0527
1975–80	−0.0464	−0.0306	−0.0204	0.0009	0.0037
1980–89	0.1012	0.0364	−0.0243	0.0097	0.0794

High school graduates					
1969–89	0.1914	0.0170	−0.0253	0.0427	0.1570
1969–75	0.1083	0.0034	0.0153	0.0404	0.0492
1975–80	−0.0566	−0.0144	−0.0356	−0.0007	−0.0059
1980–89	0.1397	0.0280	−0.0050	0.0030	0.1137
College graduates					
1969–89	0.1650	−0.0146	−0.0243	0.0754	0.1285
1969–75	0.1678	0.0967	0.0176	0.0561	−0.0026
1975–80	−0.0176	0.0090	−0.0432	0.0019	0.0147
1980–89	0.0148	−0.1203	0.0013	0.0174	0.1164

Note: Components are calculated using the distribution accounting method in Juhn, Murphy, and Pierce (1993). Values reported above are three-year moving averages around the years indicated. *X*'s include age, age squared, experience, experience squared, experience cubed, indicators for female, black, other nonwhite race, marital status, SMSA status, high school graduate, college graduate, region dummies, and a constant. *Z*'s include the DOT skill measures cognitive, motor, people, strength, and their interactions. See text for more discussion in calculation of these components.

It remains to be seen, however, how quantitatively important the effects of changes in the wage returns to skills are to explain residual inequality. For that, we use the full distributional accounting framework proposed in Juhn, Murphy, and Pierce (1993). As discussed in Section II, we write the wage equation as:

$$\text{(4)} \quad \log w_{it} = \{X_{it}\overline{\beta} + Z_{it}\overline{\gamma}\} + \{X_{it}(\beta_t - \overline{\beta})\} + \{Z_{it}(\gamma_t - \overline{\gamma})\} + \\ + \{\overline{F^{-1}}(\theta_{it}|X,Z) + (F^{-1}(\theta_{it}|X,Z) - \overline{F^{-1}}(\theta_{it}|X,Z))\}$$

where anything denoted by a bar is the average of that parameter or set of variables over time, θ_{it} is the percentile of individual i at time t in the residual distribution of Equation 1, and F is the cumulative distribution of the residuals in the same equation. In the equation above, the terms inside the first brackets capture the effects of changes in the explanatory variables, both the measures available in the CPS data (X_{it}) and the DOT skills (Z_{it}), on the wage distribution. The terms inside the second and third brackets capture the effects of the estimated changes in the prices of these explanatory variables (β_t and γ_t) on the wage distribution. Finally, the terms inside the last brackets capture the effect of changes in the distribution of wage residuals. Once we compute the effects of each of these components on the wage distribution, we measure their impact on the 90th to 10th percentile. Columns 3–6 in Table 10 show the results.

The first panel in Table 10 shows that, for the sample with all education groups and for the entire period, changes in the wage returns to cognitive, motor, and people skills as well as physical strength explain 25 percent of the observed rise in residual inequality. Note that even though we obtain these results using workers in all education groups the analysis contains education dummies and controls for other workers' characteristics so that it captures the effects of skill prices on residual inequality.

The other panels show the decomposition by education group. As expected, for workers with less than a high school degree, changes in the wage returns to skills did not contribute to rising residual inequality. Indeed, for this group, virtually all the observed rise in inequality was due to unobserved factors. Among high school graduates, changes in the prices of the DOT skills explain 22 percent of the rise in residual inequality if we look at the entire period. Looking at subperiods, we find that changes in DOT prices explain 38 percent of the rise in inequality that took place in the first half of the 1970s but none of the rise that happened in the 1980s. For college graduates, changes in the wage returns to DOT skills explain more than 40 percent of the increase in residual inequality in the whole period. For this group of workers, virtually all the increase in residual inequality occurred in the first half of the 1970s.

In conclusion, the estimated changes in the wage returns to cognitive, motor, and people skills as well as physical strength are quantitatively important in explaining the increase in residual inequality observed in the U.S. labor market. For the entire sample, we find that changes in these wage returns alone explain around 25 percent of the rise in inequality. For high school and college graduates, they account for more than 20 and 40 percent, respectively. This confirms previous findings (for example, Katz and Autor 1999) that changes in skill prices contributed to rising residual inequality.

VI. Returns to Skills and the Male-Female Wage Gap

Could changes in the wage returns to skills also be behind the narrowing of the male-female wage gap?[11] We use here a logic similar to the one applied in the previous section. If females are in occupations intensive in cognitive and people skills as compared to males, the estimated increase in the price of cognitive and people skills and decline in the price of motor skills could explain why female wages have been catching up with male wages, even without relying on segmented labor markets.

Figure 1 shows the cognitive to motor ratio of males and females for different education groups at different points in time. Throughout the period, women moved into cognitive-intensive occupations at a faster pace than men. For college graduates, for example, the ratio of cognitive to motor skills in occupations held by women went from 1.07 in 1970 to 1.14 in 1990. For men, the equivalent number went from 1.14 in 1970 to 1.13 in 1990. For high school graduates, females went from being in occupations requiring a ratio of cognitive to motor skills of 0.98 in 1970 to 1.06 in 1990, while the same measure for men went from 1.00 in 1970 to 1.01 in 1990. As a result, by 1980, women at all education levels were in occupations more cognitive intensive than men. The same happens with the people to motor skills intensity of male and female jobs. Therefore, since 1980, the estimated changes in the wage returns to skills may certainly have contributed to the narrowing of the male-female wage gap. Recall that, while the male-female wage gap had remained stable since World War II, it narrowed during the 1980s.

The question thus becomes a quantitative one. We turn again to the Juhn, Murphy, and Pierce (1993) decomposition but now focus on the effects of changes in the explanatory variables, their prices, and unobserved components on the average wages of males and females.

The first column in Table 11 shows the observed changes in the male-female wage gap over the 1970s and the 1980s for the entire sample as well as within education groups. It confirms previous findings in the literature that the wage gap declined significantly for all education groups in the 1980s, although there was not much change before then (for example, Katz and Autor 1999 and Altonji and Blank 1999).

The remaining columns in Table 11 show the components of the Juhn, Murphy, and Pierce (1993) decomposition for the gender wage gap. For the entire sample, the estimated changes in wage returns to DOT skills explain around 20 percent of the narrowing of the gender gap in the 1980s. In contrast, changes in prices of other characteristics such as education and experience do not explain any of the convergence of male and female wages, both for the overall sample and by education group. This confirms previous findings in the literature. Meanwhile, changes in unobserved characteristics contributed to the widening of the gender gap.

Changes in observed characteristics account for the largest part of the narrowing of the gender gap. As discussed before, women moved into cognitive- and people-

11. See Blau and Kahn (1997) and Altonji and Blank (1999) for detailed discussions on the patterns of changes in the male-female wage gap and their possible drivers during the period considered in our sample.

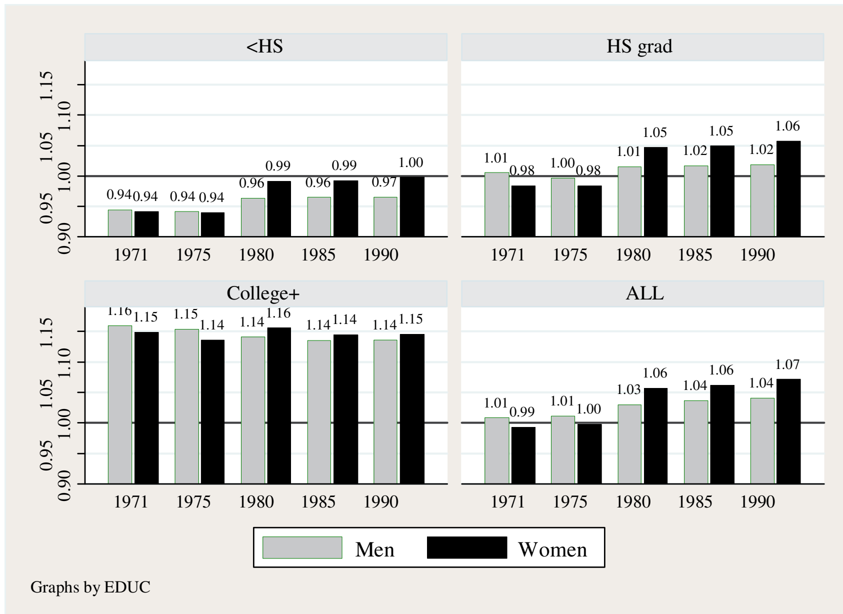

Figure 1
Cognitive to Motor Ratio

intensive occupations throughout the period, and this is part of what is being captured by changes in observed characteristics. The other part captures the well-known increase in experience and education of women in the labor force (for example, Blau and Kahn 1997).

When we look at different education groups, a similar pattern emerges. For workers with less than a high school degree, changes in the wage returns to skills explain 19 percent of the observed narrowing of the gender gap, while for high school and college graduates they explain about 22 and 12 percent, respectively.

Before concluding, it is worth noting that our empirical model assumes that labor markets are not segmented across worker characteristics, in particular across gender. This may not be the case for a number of reasons. For instance, although it is possible that the observed changes in the occupations held by men and women reflected changes in individual tastes, it is also possible that they reflected changes in discrimination and the constraints that women faced in the labor market or in premarket human capital acquisition. If this is the case, labor markets were segmented and men and women faced different returns to skills. Some models in the gender gap literature address this possibility by having the prices of skills and worker characteristics differ by gender.[12] However, the estimated returns to skills paid to

12. See Jarrell and Stanley (2004) for meta-regression analyses on this literature.

Table 11
Components of Changes in the Gender Wage Gap, Common Prices Across Gender

Period	Total Change	Observed Quantities (X,Z)	Prices of Observed Quantities Except DOT Skills (β)	Prices of DOT Skills (γ)	Unobserved Prices and Quantities
All sample					
1969–79	−0.0334	−0.0601	−0.0034	0.0169	0.0132
1979–89	−0.1194	−0.1158	−0.0012	−0.0208	0.0184
Less than high school					
1969–79	−0.0508	−0.0879	−0.0060	0.0333	0.0098
1979–89	−0.1147	−0.0988	−0.0133	−0.0215	0.0188
High school graduates					
1969–79	−0.0438	−0.0819	0.0025	0.0258	0.0098
1979–89	−0.1183	−0.1132	−0.0016	−0.0252	0.0216
College graduates					
1969–79	0.0590	0.0677	−0.0027	−0.0036	−0.0024
1979–89	−0.0992	−0.1064	0.0017	−0.0121	0.0177

Note: Components are calculated using the distribution accounting method in Juhn, Murphy, and Pierce (1993). Values reported above are three-year moving averages around the years indicated. *X*'s include age, age squared, experience, experience squared, experience cubed, indicators for black, other nonwhite race, marital status, SMSA status, high school graduate, college graduate, region dummies, and a constant. *Z*'s include the DOT skill measures cognitive, motor, people, strength, and their interactions. See text for more discussion in calculation of these components.

men and women may differ because of unobserved worker heterogeneity that is correlated with gender, even if markets were not segmented. An alternative way of dealing with the possibility of market segmentation is to estimate skill prices on a male-only sample (see, for example, the preferred specification in Blau and Kahn 1997). As long as changes in discrimination or other sources of market segmentation do not affect the male reward structure, the estimates on a men-only sample will provide skill prices in a nondiscriminatory labor market. As discussed in Section IVC, our robustness checks find that the main pattern of results holds when we control for worker selection and also when we estimate skill prices on a men- and white men-only samples. Indeed, the few instances when the results differ across samples were in the 1970s, not the 1980s, the decade when most of the narrowing of the gender gap occurred. Thus, our findings show that changes in the prices of motor, cognitive, and people skills can help explain the narrowing gender gap even in the absence of changes in differential treatment of men and women in the labor market.

To summarize, we confirm that changes in observed women's relative levels of labor market qualifications and occupational choices explain a large part of the observed narrowing of the gender wage gap. However, we show that changes in the prices of cognitive, people, and motor skills also contributed significantly to the narrowing of the gender gap in the 1980s.

VII. Conclusion

In this paper, we estimate the wage returns of a multidimensional vector of workers' skills at their jobs. This vector includes measures of the worker's cognitive, motor, and people skills as well as physical strength. In contrast with the prevailing view of a general increase in the returns to all types of skills (for example, Bound and Johnson 1992; Katz and Murphy 1992; Juhn, Murphy, and Pierce 1993), we show that during the 1968–90 period, the returns to cognitive and people skills increased while the returns to motor skills declined. We also show that people skills did not become more valuable by themselves but by becoming more complementary to cognitive and motor skills.

We then show that the estimated changes in skill prices can help explain the two major trends characterizing the U.S. labor market during the 1970s and 1980s—rising inequality and a narrowing of the male-female wage gap. We show that the top of the wage distribution within college and high school graduates was in occupations intensive in cognitive and people skills while the bottom was in motor-intensive jobs. Therefore, the estimated skill price changes increased the wage dispersion within these two education groups. Also, we show that by 1980 women of all education levels were in more people- and cognitive-intensive occupations relative to men. Therefore, these changes in skill prices also contributed to narrowing the gender wage-gap. Quantitatively, they account for 20 to 40 percent of the observed changes in residual inequality for different education groups and for around 20 percent of the narrowing in the gender gap in the 1980s.

Finally, it is important to note that although it is appealing to speculate on the sources of the estimated changes in skill prices (for example, supply versus demand factors), it is clearly beyond the scope of our paper. Some studies provide evidence that changes in skill demand were likely to be more important than in skill supplies (for example, Autor, Levy, and Murnane 2003), but finding the ultimate drivers of the observed changes in skill prices is still very much an open question.

References

Acemoglu, Daron. 2002. "Technical Change, Inequality, and The Labor Market." *Journal of Economic Literature* 40(1):7–72.

Altonji, Joseph, and Rebecca Blank. 1999. "Race and Gender in the Labor Market." In *Handbook of Labor Economics, Vol. 3C,* eds. Orley Ashenfelter and David Card, 3143–251. North-Holland Elsevier Science.

Autor, David H., Frank Levy, and Richard Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics* 118 (4):1279–1333.

Black, Sandra E., and Alexandra Spitz-Oener. 2007. "Explaining Women's Success: Technological Change and the Skill Content of Women's Work." NBER Working Paper 12116.

Blau, Francine, and Lawrence Kahn. 1997. "Swimming Upstream: Trends in the Gender Wage Differential in the 1980s." *Journal of Labor Economics* 15(1, pt 1):1–42.

———. 2006. "The U.S. Gender Pay Gap in the 1990s: Slowing Convergence." *Industrial and Labor Relations Review* 60(1):45–66.

Borghans, Lex, Bas ter Weel, and Bruce Weinberg. 2006. "People People: Social Capital and the Labor-Market Outcomes of Underrepresented Groups." NBER Working Paper 11985.

Bound, John, and George Johnson. 1992. "Changes in the Structure of Wages in the 1980s: An Evaluation of Alternative Explanations." *American Economic Review* 82(3):371–92.

Current Population Survey, March 1968–90. 2001. CPS Utilities, Santa Monica, Calif.: Unicon Research Corporation [producer and distributor].

Ingram, Beth, and George Neumann. 2006. "The Returns to Skill." *Labour Economics* 13(1):35–59.

Jarrell, Stephen B., and T. D. Stanley. 2004. "Declining Bias and Gender Wage Discrimination? A Meta-Regression Analysis." *The Journal of Human Resources,* 39(3):828–38.

Juhn, Chinhui, Kevin Murphy, and Brooks Pierce. 1993. "Inequality and the Rise in Returns to Skill." *Journal of Political Economy* 101(3):410–42.

Katz, Lawrence, and David Autor. 1999. "Changes in the Wage Structure and Earnings Inequality." In *Handbook of Labor Economics, Vol. 3A,* eds. Orley Ashenfelter and David Card, 1463–558. North-Holland Elsevier Science.

Katz, Lawrence, and Kevin Murphy. 1992. "Changes in Relative Wages, 1963–1987: Supply and Demand Factors." *Quarterly Journal of Economics* 107(1):35–78.

Miller, Anne, Donald Treiman, Pamela Cain, and Patricia Roose, eds. 1980. *Work, Jobs and Occupations: A Critical Review of the Dictionary of Occupational Titles*. Washington, D.C.: National Academy Press.

Moulton, Brent R. 1990. "An Illustration of the Pitfall of Estimating the Effects of Aggregate Variables on Micro Units." *Review of Economics and Statistics* 72(2):334–38.

Mulligan, Casey, and Yona Rubinstein. 2004. "The Closing of the Gender Gap as a Roy Model Illusion." NBER Working Paper 10892.

———. 2005. "Selection, Investment, and Women's Relative Wages since 1975." NBER Working Paper 11159.

National Academy of Science, Committee on Occupational Classification and Analysis. 197? and 2001. Dictionary of Occupational Titles (DOT): Part II-Fourth Edition Dictionary of DOT Scores for 1970 Census Categories [Computer file], ICPSR 7845, Washington, D.C.: U.S. Department of Commerce, Bureau of the Census [producer], Ann Arbor, Mich.: Inter-University Consortium for Political and Social Research [distributor].

Spenner, Kenneth I. 1983. "Deciphering Prometheus: Temporal Change in the Skill Level of Work." *American Sociological Review* 48(6):824–37.

U.S. Department. of Labor, U.S. Employment Service, and the North Carolina Occupational Analysis Field Center. 1991 and 1994. Dictionary of Occupational Titles (DOT): Revised Fourth Edition, 1991 [Computer File], Washington, D.C.: U.S. Department of Labor, U.S. Employment Service, and Raleigh, NC: North Carolina Occupational Analysis Field Center [producers], Ann Arbor, Mich.: Inter-University Consortium for Political and Social Research [distributor].

Welch, Finis. 2000. "Growth in Women's Relative Wages and in Inequality among Men: One Phenomenon or Two?" *American Economic Review Papers and Proceedings* 90(2):444–49.

Witt, Mary, and Patricia K. Naherny. 1975. "Women's Work: Up from .878." Report on the DOT Research Project, Madison: University of Wisconsin Extension, Women's Educational Resources.

Wolff, Edward E.. 2003. "Skills and Changing Comparative Advantage." *The Review of Economics and Statistics* 85(1):77–93.