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The Strength of Occupation Indicators as a Proxy for Skill

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“The Strength of Occupation Indicators as a Proxy for Skill”*

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Abstract

Labor economists have long used occupation indicators as a proxy for unobserved skills that a worker possesses. In this paper, we consider whether inter-occupational wage differentials that are unexplained by measured human capital are indeed due to differences in often-unmeasured skill. Using the National Compensation Survey, a large, nationally- representative dataset on jobs and ten different components of requisite skill, we compare the effects on residual wage variation of including occupation indicators and including additional skills measures. We find that although skills do vary across 3-digit occupations, occupation indicators decrease wage residuals by far more than can be explained by skill differentials. This indicates that "controlling for occupation" does not equate to controlling for skill alone, but also for some other factors to a great extent.

Additionally, we find that there is considerable within occupation variation in skills, and that the amount of variation is not constant across skill levels. As a result, including occupation indicators in a wage model introduces heteroskedasticity that must be accounted for. We suggest that greater caution be applied when using and interpreting occupation indicators as controls in wage regressions.

I. Introduction

Occupations play a central role in labor markets. People get both formal education and on-the-job training to develop sets of skills that enable success in different categories of jobs. Those categories are occupations. Occupation classifications are used by both firms and workers to facilitate communication about the content of a job, which promotes more efficient screening of potential job applicants than otherwise might occur. The job requirements associated with any given occupation (e.g. doctor, lawyer, accountant, laborer, secretary, teacher, computer programmer) also provide a road map for those seeking to enter the occupation, whether by formal schooling, on the job training, or both. Without occupation classifications, therefore, there would be much less efficient resource allocation in the labor market.

Despite this central role for occupations, there is no consensus within labor economics on the issue of how to use occupation classifications empirically. On the one hand, the conceptual argument for occupations as bundles of skills leads some economists to use occupation controls to hold constant unobserved skill differences, particularly when estimating human capital earnings or other labor market models. On the other hand, because people can and do switch occupations, and wages are presumed to be set at least partially by supply and demand, there are risks in viewing occupational wages as direct measures of the returns to skill.[1] For example, do doctors earn more than laborers because they have more skill, because of barriers to entry, or both? Clearly doctors learn real skills in medical school, so the occupational classifications represent more than just barriers to entry. Yet there also are barriers to entry created both naturally by the need for lengthy graduate education and on-the-job training, and artificially by

[1] Also, because there is substantial occupational segregation along gender and racial lines, and that segregation is correlated with wages, there is intense debate whether occupations in these cases are proxies for true skills or for nonmarket factors (including discrimination) that are unrelated to skill.

licensing requirements. Thus the question is to what extent are occupations proxies for skills versus a convenient way of classifying jobs that is unrelated to objective measures of skills?

While this question is critical for understanding the role of occupations (and skills) in the labor market, traditional data sets in economics are not suitable for the task because they only record occupation title and demographic characteristics of the person holding the job. This paper uses the National Compensation Survey (NCS), a new nationally-representative data set with measures of skill that are based on the job to examine this question in depth. The skill measures are derived from the behavioral science literature on job design, which uses concepts such as complexity of the job and degree of autonomy to compare and rate dissimilar jobs throughout the economy using uniform measurements. We are thus able to compare the effects on wage estimations of including occupation indicators as a proxy for unobserved skill versus using direct measures of those skills.

We find that although skills do vary across 3-digit occupations, occupation indicators decrease wage residuals by far more than can be explained by skill differentials. This indicates that "controlling for occupation" does not equate to controlling for skill alone, but also for some other factors to a great extent. Part of the inter-occupation wage variation is due to nonrandom sorting along demographic lines: gender and race controls decrease the residual wage variation that is not explained by the NCS skill controls but which is accounted for by occupation controls. Additionally, we find that there is considerable within occupation variation in skills, and that the amount of variation is not constant across skill levels. As a result, including occupation indicators in a wage model introduces heteroskedasticity that must be accounted for. We suggest that greater caution be applied when using and interpreting occupation indicators as controls in wage regressions.

The paper is structured as follows. In the next section we review the development of the occupation classification system and the extent to which skills have not been a main organizing logic for dividing jobs into similar groups. The next sections describe the NCS data and compare human capital earnings models estimated using the NCS and Current Population Survey (CPS). Following that we focus on the amount of residual inter-occupational wage variation that is accounted for by the NCS skill measures. The final section examines how including traditional occupation controls beyond the NCS skill measures introduces heteroskedasticity in human capital earnings models.

II. A brief history of the occupation classification system

> "It should be the purpose of statistics of occupation… [to] show, so far as possible, not only the skill and intelligence of the worker, and his position in the industry,…but, as a means for the study of the risk, healthfulness, and numerous other problems connected with his occupation, they should show, also, the specific services rendered, work done, or processes performed by him" (Alba M. Edwards, 1911)

In the nineteenth century, occupational classifications generally focused on the industry in which a worker was employed. For example, one category in the 1880 Census occupation system is car makers, which clearly involves many different skills and types of tasks. In fact, there are nearly 100 distinct manufacturing and professional occupations that contribute to *making cars* today. On the other hand, the 1880 Census also contained separate categories for "clerks in stores", "bookkeepers in stores", "clerks and bookkeepers in banks", "clerks and bookkeepers in companies", "clerks and bookkeepers in offices" and "clerks and bookkeepers in railroad offices", all of whom presumably possess similar skills and perform similar tasks.

In arguing for a major revision of the Census method of classifying occupations, Alba Edwards (1911, 1938, 1941) proposed that a worker should be classified not by the product she was making, but by the kind of work she was doing or service she was rendering. He argued that since the aim of collecting statistics is to "better the social and economic condition of man" that such statistics should, in fact, measure this condition. The Census Bureau first fully adopted this methodology in the 1940 Decennial Census. At the same time, Edwards also realized that no perfect categorization of occupations is possible, both because the division of labor and vast number of industries in the economy prohibits a categorization that is both "sufficiently broad and sufficiently detailed", and because the occupations are not always well-defined and change over time as "new processes in manufacturing are being devised." (Edwards, 1911: 619-20)

Labor economists often control for the effect of otherwise unobserved human capital on wages by including a series of occupation indicator variables in a wage regression, on the assumption that occupation categories measure the skills a worker must have to perform a particular job in that occupation. It is not certain, however, that the occupational classification system successfully distinguishes the skills of workers. First, it may not have correctly distinguished initial skill differences between occupations in 1940. As Margo Conk (1978) notes, "Without providing an adequate definition of 'skill' or a criterion for determining it, the United States Census began to classify occupations according to skill. To do this, the Census fell back on the 'social' component of its definition of an occupation, in short, on the divisions of ethnicity, race, sex and age within the American population." Thus, an occupation might be categorized as unskilled merely because there were many minority or female workers in the occupation.

The second problem with inferring skill from occupational classifications is that there is significant within-occupation skill variation that is entirely obscured by the Census classification. Certainly, there are differences among workers in their ability to perform tasks of high complexity, and there are differences among jobs in the level of task complexity and responsibility bestowed on the worker. It is harder, for example, to build an entire house than to install a bookshelf, yet the people who do part of that work in both cases are classified as carpenters by the Census. A copy editor for children's books may require less knowledge than one responsible for scientific texts. And a police officer in a quiet rural area faces quite different job demands than one in a high crime urban area. In each case the job demands differ significantly within occupations (even "narrowly" defined 3 digit occupations), and so, too, might the skills of the people who work in those jobs.

The third potential difficulty with inferring skill from occupational classifications is that both the mean skill level and the variation in skill within an occupation can change over time without being captured by changes in the occupational classification system adjustments. As technology changes the nature of the production methods, jobs become up-skilled or down-skilled, depending on the nature of the technology (see, for example, Autor, Levy and Murnane, 2002) This can lead to an occupation category becoming more skilled, less skilled, or having a higher variation in skill over time.

III. The National Compensation Survey

The National Compensation Survey (NCS) is a restricted-use dataset of information on up to 20 jobs each at nearly 20,000 nationally representative establishments in the non-farm, non-Federal U.S. economy in 1999. The data are collected by field economists who visit sampled establishments and randomly select 5-20 workers from the site's personnel records, depending on establishment size. Through interviews with human resources representatives, detailed information about the jobs those workers hold is obtained.

The data include information on the establishment, including its location, industry, whether privately or publicly owned, and whether operating for profit. In addition, for the selected jobs, data are collected on unionization status, work hours, incentive pay, occupation and earnings. The NCS data measure the skills and wages of jobs—thus they do not measure anything about a particular worker who might hold that job. There are therefore no demographic details about workers. Rather than measuring the human capital stock possessed by a worker, as proxied by his education level and experience, the NCS measures the human capital requirements of a given job. These requirements are encompassed by ten "generic leveling factors," which are intended to measure various job design attributes consistently across occupations. These factors are based on the Federal Government's Factor Evaluation System, which is used to set Federal pay scales,[2] and are measured on Likert scales with ranges varying from 1-3 to 1-9.

- Knowledge (1-9): The nature and extent of applied information that the workers must possess to do acceptable work. The lowest numbers correspond to blue collar jobs, requiring minimal skills or education; the highest numbers correspond to very high-skilled jobs.
- Supervision Received (1-5): The nature and extent of supervision and instruction exercised by the supervisor, the extent of modification and participation permitted by the employee, and the degree of review of completed work. Larger values correspond to *less* supervision.

[2] For a detailed description of the NCS, see Pierce (1999).

- Guidelines (1-5): How specific and applicable the guidelines are for completing the work, and the extent of judgment needed to apply them. Larger numbers correspond to *less* use of guidelines.
- Complexity (1-6): The nature, number, variety, detail and originality of the tasks, and the difficulty in determining what needs to be done. Larger numbers correspond to more complex jobs.
- Scope and Effect (1-6): The extent to which the nature of the work impacts the work, output or service of others within or outside the organization. Larger numbers correspond to greater impact on other activities and persons.
- Personal Contact (1-4): Extent of contacts with persons not in the supervisory chain, including the difficulty of initiating and performing communication. Larger numbers correspond to more contacts or higher-ranking contacts.
- Purpose of Contacts (1-4): Nature of contacts, ranging from exchange or clarification of information to justifying, defending or negotiating matters involving significant or controversial issues. Larger numbers correspond to more significant contacts.
- Physical Demands (1-3): Physical abilities and exertion involved in the work. Larger numbers correspond to more physical demands.
- Work Environment (1-3): Risks and discomforts in the physical surroundings or the nature of the duties. Larger numbers correspond to more discomfort or risk.
- Supervisory Duties (1-5): Level of supervising responsibility. Larger numbers correspond to more levels of subordinates supervised.

Table 1 shows the distribution of values of the skill measures. To better compare across skills, Table 1 also includes the mean of each variable, normalized to range from zero to one.

These statistics show that most jobs have very minimal supervisory duties. There are few jobs with severe physical demands or extremely risky or uncomfortable work environments. For the remaining skills, there are few jobs in either the lowest or the highest skill categories.

IV. Estimating human capital earnings models using CPS vs. NCS

The canonical human capital earnings model uses schooling and imputed experience to infer the person's skill level. Over the years labor economists have used a variety of more direct measures of skill, particularly scores from "objective" measurement tools such as the IQ test and the Armed Forces Qualifying Test, to show that traditional human capital measures are positively correlated with these measures of skill. The problem with these measures, however, is that they are focused on the individual's innate skills, not the job requirements. Thus they are suitable for isolating the portions of earnings that are due to fixed factors related to the individual. They are not, however, good measures of the skill requirements of the jobs themselves.

The NCS job skill most closely related to traditional worker's human capital measures is knowledge, which is typically coded as that which "would be acquired through a pertinent [degree] or its equivalent in experience, training, or independent study". To see how a worker's human capital measures compare to the knowledge requirements of the jobs those workers hold, we obtain the average knowledge required for NCS jobs in each three-digit occupation and compare this to the average education and years of potential experience for workers in those occupations in the March 2001 Current Population Survey. The correlation between knowledge and education is .824, while the correlation between knowledge and potential experience is only .080[3]. Table 2 summarizes this comparison, aggregating the numbers to the 2-digit occupation

[3] Interestingly, the correlation between the average education and average potential experience is -.0783.

level. In general, many of the occupations are ranked similarly along knowledge and education. It is less apparent for knowledge and potential experience that the two measure a similar concept. In many particular occupations, such as secretary, mail distribution, building and personal services, vehicle and machine operating, the workers have many years of potential experience, while the jobs do not require a high amount of knowledge. In these jobs, the additional years of potential experience do not result in accumulating additional human capital relevant to performing this job.

We consider whether knowledge plays a similar role to traditional human capital variables in predicting wages by estimating a wage model in the CPS using only education, and potential experience and its square as explanatory variables, and estimating a wage model in the NCS using only knowledge. Table 3 shows the results of these estimations. The explanatory power of the NCS model is much higher than that of the CPS model. In both samples we predict log hourly wages and calculate the average within each 3-digit occupation code. The correlation between these two sets of predicted wages is quite high – .87, suggesting that the measures, although somewhat different, do explain wages comparably for the average worker.

We are interested not only in the explanatory power for the average worker, however, but also in the relative explanatory power across occupation groups. Figure 1 shows both the CPS and the NCS residuals of these estimations, averaged across all workers/jobs in each 3-digit occupation code. The data points are sorted in an approximate white collar-blue collar order, with executives and managers on the far left and unskilled laborers on the far right. As indicated earlier by the R-squareds of Table 3, neither model fully explains wage variation, but the NCS model that controls for knowledge requirements results in smaller overall residuals than the CPS model that controls for accumulated human capital. In both samples there are important differences across 3-digit occupations in the explanatory power of the human capital controls. In the CPS, accumulated human capital explains less variation in both the high skill occupations and also in the production occupations. In the NCS, knowledge explains less variation for the production workers.

V. Occupational indicators as a proxy for unobserved skill

Such findings of inter-occupational wage differentials that are not explained by differences of worker's observed human capital are common. In fact, such wage differentials motivate the inclusion of occupation indicators in many empirical wage estimations. This makes sense if worker ability is poorly measured and the omitted ability variable varies systematically across occupations. When occupation controls are included, oftentimes along with other "job" controls like industry[4] and union status, they typically account for a significant portion of wage differentials in both gender (Blau and Kahn, 2000) and part-time (Blank, 1990) wage regressions. On the other hand, occupation indicators may control for other non-market factors that affect wages, including, but not limited to, discrimination and sorting on the basis of nonmarket characteristics.

If we believe that ability is the only unobserved variable, then we believe that wages are given by the following wage model:

(1) $W_j = \beta_0 + \beta_1 X_j + \beta_2 Z_j + u_j$

where W_j is the wage rate earned in job j, X_j is the observed component of human capital in job j, Z_j is the unobserved component of human capital and u_j is a random disturbance that is distributed $N(0,\sigma_u^2)$. It is well established that estimating model (1) without controlling for the

[4] Occupation controls sometimes are entered by themselves, other times in conjunction with controls for industry. However, because there are only a limited number of occupations represented within many industries (Helwege, 1992), the identification of either when both are included is driven from a minority of industry-occupation groups.

unknown variable Z_j results in biased estimates of β_1. To improve upon our estimate of β_1, we use a set of occupation indicators as a proxy for the unknown data, where the occupations are related to Z_j by:

(2) $Z_j = \gamma_0 + \gamma_1(occ=1) + \gamma_2(occ=2) + \ldots + \gamma_N(occ=N) + v_j$

where v_j represents the measurement error in the proxy, or the extent to which occupation indicators are a "good" proxy for unobserved ability. Generally we cannot observe this relationship, and must assume that the error is distributed $N(0, \sigma_v^2)$. This leads us to estimate:

(3) $W_j = \beta_0 + \beta_1X_j + \beta_2[\gamma_0 + \gamma_1(occ=1) + \gamma_2(occ=2) + \ldots + \gamma_N(occ=N) + v_j] + u_j$

or ,

(4) $W_j = (\beta_0 + \beta_2\gamma_0) + \beta_1X_j + \beta_2(\gamma_1(occ=1) + \gamma_2(occ=2) + \ldots + \gamma_N(occ=N)) + (u_j + \beta_2v_j)$

Absent any measurement error, estimation of the model (4) would yield unbiased estimates of β_1. Even with measurement error, the bias will be smaller in estimating equation (4) than if we simply left unmeasured the omitted variable. Generally, we would interpret significance of the coefficients on the proxy to mean that the unobserved skills are correlated with the wages, although we could not separate β_2 and γ_n. Caution should be exercised in such interpretation of this model, however. In particular, suppose that another unobserved variable, D_j, is important to determining wages, so that:

(5) $W_j = \beta_0 + \beta_1X_j + \beta_2Z_j + \beta_3D_j + u_j$

where the unobserved variable D_j is likewise related to the occupation indicators by:

(6) $D_j = \alpha_0 + \alpha_1(occ=1) + \alpha_2(occ=2) + \ldots + \alpha_N(occ=N) + w_j$

with w_j again representing the measurement error in the proxy. Then the wage model we estimate is actually:

(7) $W_j = (\beta_0 + \beta_2\gamma_0 + \beta_3\alpha_0) + (\beta_2\gamma_1 + \beta_3\alpha_1)(occ=1) + \ldots + (\beta_2\gamma_N + \beta_3\alpha_N)(occ=N) + error$

which is completely undistinguishable from equation (4). Thus, we may attempt to interpret the significance of the occupation indicators and the increased overall explanatory power of the model, as an indication that we have "controlled" for unobserved skill differences, but we may just as likely have, in fact, controlled for some other non-market characteristics of jobs that vary across occupations as well.

Before we can address this issue, we first show the bias in estimating the wage model (1) without any proxy for the unobserved skills, and then show how the coefficient on knowledge and the explanatory power of the model change when we add a full set of 3-digit occupation indicators. In addition to knowledge, we include an indicator for whether the job is a part-time job, an indicator for whether it is unionized, and an indicator for whether it earns incentive pay. It is important to remember that these variables are characteristics of the job, not of any particular worker who performs the job. In addition to these job features, we include the log of the establishment size, indicators for whether the establishment is a non-profit institution, and indicators for whether the establishment is located in the Northeast, Midwest or South regions. After controlling for these job and workplace features, we then add a full set of indicators for each 3-digit occupation.

Table 4 compares these two estimations. Adding the explanatory variables reduces the size of the knowledge coefficients and increases the overall explanatory power by 5%. The inclusion of occupation indicators further reduces the measured effect of knowledge and increases the adjusted R-squared from .747 to .807[5]. Figure 2 shows the dramatic change in the pattern and size of the wage residuals resulting from including occupation indicators in the wage estimation. The mean of the average wage residuals is now quite close to zero, and the

[5] Due to the extremely large sample size, standard errors of the coefficient estimates are quite small for all variables and we do not report them here.

differences in explanatory power across occupations is largely eliminated. Including occupations clearly improves the ability of the model to predict the inter-occupation wage differentials that are evident in the data and are not explained by human capital.

Again, it is not at all clear how to interpret this method of "explaining" wage variation across occupations. On the one hand, unobserved skills may vary across occupation, and the inclusion of indicators for the worker's/job's occupation may be capturing the effect of such omitted variables. If this is the case, it seems quite reasonable to use occupation indicators as a proxy for the unobserved variables. On the other hand, if the wage differentials are due to other non-market features of a worker/job, it is important for the researcher to know that the occupation indicators are not proxies for unobserved skills, but rather for differences across occupation in some other variable.

With most data on worker demographics, it is not possible to distinguish between these two alternatives, because the skill variables are unobserved. Using the NCS data, however, we can investigate the relationship between occupation indicators and some of these often-unobserved requisite job skills. In addition to knowledge, the NCS contains nine additional measures of job skill that are not necessarily captured by traditional human capital variables. In order for occupation indicators to capture these omitted skills, the skills must, in fact, vary systematically across occupations. Figures 3A-I show the average value of each skill within a 3-digit occupation group. In a sense, these graphs indicate the estimated γs from equation (2). There is considerable variation across occupations. For supervision received, guidelines, complexity and scope and effect, the means are highest for managers, professionals and technical jobs. Sales, clerical and most service jobs have fairly low values of these skills. Construction and precision craft workers have intermediate values, while the machine operators, assemblers and other laborers have the lowest values. Personal contacts and the purpose of those contacts have high values only for the managers, professionals and technical workers, and are consistently low across most administrative, service and production jobs. Physical demands and work environment are similarly low for most managers, professionals, technical, sales and clerical jobs, and higher for those in services and production. Lastly, supervisory duties are quite high for the executive managers, much lower for professional and technical jobs, and at their lowest for all other groups, with the exception of occupation codes that are specifically designated as "supervisory", such as administrative supervisors and construction supervisors. The patterns in these figures do suggest that often-unmeasured skills such as these do, in fact, vary systematically across occupation and may provide justification for including occupation indicators to control for these omitted skill variables.

To further investigate whether occupation indicators serve as a proxy for such omitted skills, we consider how adding the skills to a wage regression affects the overall explanatory power of the model, as well as the relative explanatory power across occupations. We expect that including additional skills in a wage regression will not only push the average residual toward zero, but will also flatten out the distribution of those residuals across occupation groups. To the initial wage model showed in column one of Table 4, we add each of the nine skills, first one at a time and then all simultaneously. In each case we use a set of indicator variables for each Likert value the skill takes on.

The resulting adjusted R-squareds are shown in Table 5. For supervision received, guidelines, complexity and scope and effect, the overall adjusted R-squared of the wage model increases with their addition. The remaining four skill requirements do not add to the explanatory power of the model. Not only do the skill requirement variables improve the fit of the model, but even after controlling for occupations, these variables still matter, although the change in adjusted R-squared is small. This indicates that there are aspects of skill not represented by the traditional occupation classifications. On the other hand, the large amount of additional residual variation explained by the occupation indicators after controlling for the full set of NCS skills indicates that something other than skills as measured by traditional human capital and the other NCS factors is driving differences in mean wages across occupations.

One possible nonmarket factor that occupations may proxy for, but that may be unrelated to skill is the gender or race of the worker. The NCS data do not contain any demographic information on the workers who hold the jobs surveyed. Thus, occupation indicators may control for unmeasured gender or racial differences that affect wages. To provide some evidence on this question, we calculate from the March CPS the percent of workers that are female and the percent of workers that are non-white in each 3-digit occupation, and add the result to the wage model with controls for all skills. The explanatory power increases somewhat, owing to the significant negative coefficients on both variables. Wage differentials across gender and racial lines persist even with strong controls for skills, and this may be one nonmarket factor for which occupation indicators are controlling.

Table 5 indicates that the inclusion of additional skills increases the ability of the wage model to explain the variation in wages for the average job, although not quite as much as the inclusion of occupation indicators. As we saw in Figure 2, however, the biggest impact of the occupation indicators was in reducing the unexplained inter-occupational wage differentials. In order to compare the effect of the skills to the effect of occupation indicators, we calculate the average residuals within each 3-digit occupation and examine the distribution across occupations of these average wage residuals under each model estimated.

Table 6 shows the first four moments of this distribution for each model. Consistent with the visual representation of the residuals in Figure 2, the data indicate that the model with occupation controls has mean zero residuals, with very little variation, a slight negative skew (with several negative average residuals among the highest and lowest skill groups), and some leptokurtosis. While several of the skills also reduce the mean of these within-occupation average residuals, especially guidelines, complexity and scope and effect, even with the inclusion of all nine skills, the average remains around 0.015, while including the occupation indicators reduces the average to 2.6 E-11. Additionally, guidelines, complexity and scope reduce only slightly the amount of variation across occupations in the size of the unexplained component of wages (from .153 in the model with only knowledge to around .14). Again, this is very little reduction compared to the effect of including occupation indicators, which removes nearly all the variation across occupations, by design. Including additional skills increases the extent of negative skew and leptokurtosis in the average residuals. Unlike in the model with occupation indicators, the negative skew in these cases does not indicate more negative than positive residuals, but rather indicates that more of the average residuals lie below the (positive) mean than above, which makes sense.

To summarize, the addition of often-unmeasured job skill variables does reduce the size of the residuals somewhat, and does diminish the differences in explanatory power across occupations to a small extent. The magnitude of these effects is tiny compared to the effect of introducing occupation indicators. This suggests that for the most part, occupation indicators are controlling for factors much more important to determining inter-occupational wage differentials than the skill differentials measured here. This leaves two possibilities: there are other important skills not measured by the NCS, or inter-occupational wage differentials are due to other factors than differential skill requirements across occupations.

VI. Heteroskedasticity

One further difficulty with occupation proxies that we have not addressed is that the assumptions about the distribution of the measurement error might not hold. In particular, looking at Figures 3A-I, it appears that there is significant within-occupation variation in the level of the skills. If the amount of variation is consistent across occupations, so that $Var(v_j) = \sigma_v^2$, this is not problematic. However, the standard errors suggest otherwise for several of the skill requirements. In particular, the figures show that the within-occupation variation is highest for scientists, teachers and professors, other professionals, technicians, clerical and administrative jobs, construction jobs and precision craft jobs. This indicates that for these 3-digit occupation categories, jobs are not as similar as they are within other 3-digit occupations—especially managers, engineers, sales, supervisors, service jobs and very low-skilled jobs. If the variance of the proxy's measurement error is related to the proxy itself, then the composite error term of the wage model will also suffer from heteroskedasticity.

To assess the extent to which this is a problem, we test for heteroskedasticity in the wage estimation model that controls for knowledge, job and establishment characteristics and the occupation indicators as proxies for omitted skills. Since the patterns of within-occupation skill variability are evident in all nine measures of skill, we test whether the heteroskedasticity is a function of each measure separately as well as all measures combined. Although we perform these tests on the NCS sample, we are somewhat more concerned about the likely heteroskedasticity in a sample where occupation indicators are used in place of additional information on skill requirements beyond the standard human capital measures. To check whether this is a problem in such data, we calculate the 90-10 skill differential by 3-digit occupation in the NCS, and test whether this variable is related to the variance of the CPS wage regression. The CPS wage regression includes controls for the worker's race, gender, marital status, whether working part-time, whether a veteran, and region of residence. Table 7 shows the results of both sets of tests. There is strong evidence of heteroskedasticity in the NCS wage model with occupation controls, related to each of the skills. Even in the much weaker CPS test where the skill level can only vary across occupations, there is strong evidence of heteroskedasticity in the model that is related to several of the skills.

VII. Conclusion

In this paper, we have examined the use of occupation indicators as proxies for often-unobserved ability or job skill requirements. We use the National Compensation Survey to compare the effects on wage estimations of including occupation indicators versus including actual measures of job skills. In general, researchers cannot do this using traditional data sets because skill is often measured only by education and experience, rather than the amount of particular skills required by a job (and thus rewarded by wages).

We find that while including measures of actual job skills requirements improves the fit of a human capital earnings model, the extent of the improvement is much less than with occupation indicators. Thus, "controlling for occupation" does not appear to be the same thing as controlling for unobserved ability, but rather controlling partially for unobserved ability and to a larger extent, other factors that are also related to occupation classifications.

We also find that part of the inter-occupation wage variation is due to nonrandom sorting along demographic lines: gender and race controls decrease the residual wage variation that is not explained by the NCS skill controls but which is accounted for by occupation controls. This perhaps is not surprising given the long-running debate regarding the merits of controlling for occupation when estimating gender and race wage differentials. Our contribution to the debate is the inclusion of direct measures of skill requirements which enable a comparison with variation in gender and racial composition as factors explaining individual wage differentials. The evidence indicates that part of the residual wage variation accounted for by occupation controls is due to skill requirement differences, but part is also due to apparent non-market sorting, including sorting along gender and racial lines. Thus controlling for occupation in gender and racial wage differential models appears to over-control for skill requirements and potentially bias such models away from non-market explanations of wage differentials (e.g. due to discrimination), even when the "true" model includes non-market drivers of wage differentials.

Additionally, we find that there is considerable within-occupation variation in skills, and that the amount of variation is not constant across skill levels. As a result, including occupation indicators in a wage model introduces heteroskedasticity that must be accounted for. This is at least in part because skills are more homogenous in certain occupation categories than in other ones. This causes the measurement error in the proxy to be heteroskedastic, which affects the wage error term as well. In the absence of direct skill measures such as these in datasets like the CPS, human capital earnings models that include controls for occupation should also use heteroskedasticity-consistent standard errors.

Based on these results, we urge caution in both the use and interpretation of occupation indicators as proxies for unobserved skills. Greater efforts can and should be made to collect data on job skills, which would obviate the need for using occupation indicators. Additionally, new occupation categories might be designed that incorporate job skills data such as the NCS.

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TABLE 1. Mean and distribution of responses to leveling factors

	Normalized Mean	Raw distribution of responses								
		1	2	3	4	5	6	7	8	9
Knowledge	.401	10.5	25.7	19.9	13.5	7.0	14.4	7.2	1.6	0.1
Supervision rec'd	.449	21.6	41.5	28.8	7.1	1.0				
Guidelines	.408	33.3	36.1	24.7	5.2	0.7				
Complexity	.399	19.3	35.1	35.7	6.8	3.0	0.2			
Scope and effect	.352	30.9	34.5	28.5	4.6	1.3	0.2			
Personal contacts	.420	44.9	42.7	12.2	0.3					
Purpose of contacts	.369	62.2	28.6	8.5	0.7					
Physical demands	.528	43.7	54.0	2.3						
Work environment	.501	51.5	46.8	1.7						
Supervisory duties	.272	78.7	8.9	10.4	1.8	0.2				

TABLE 2. Human capital measures in the 1997 NCS and 2001 CPS

	NCS knowledge		CPS years education		CPS years potential experience	
	Mean	*Rank*	*Mean*	*Rank*	*Mean*	*Rank*
Health diagnostic	0.8119	1	19.281	1	21.521	18
Lawyer/judge	0.788	2	17.813	2	19.02	28
University prof.	0.7515	3	17.494	3	19.023	27
Executive	0.7342	4	14.303	16	22.99	9
Engineers	0.7325	5	15.043	12	16.805	36
Natural sciences	0.7241	6	17.092	4	17.872	34
Math/CS	0.7226	7	15.858	6	10.729	43
Public admin	0.7198	8	14.596	13	20.898	21
Health treatment	0.66	9	15.76	8	12.764	41
Mgmt-related	0.6555	10	15.19	11	19.79	25
Teachers	0.6373	11	15.564	9	22.139	12
Other professional	0.5833	12	16.321	5	20.226	23
Admin. supervisor	0.5644	13	12.763	29	23.386	8
Service sales	0.5498	14	14.361	15	21.347	20
Other technical	0.5478	15	15.815	7	30.405	1
Sales manager	0.4964	16	13.667	22	22.062	14
Finance/bus. sales	0.4902	17	14.45	14	20.366	22
Engineering tech.	0.4854	18	13.459	24	18.86	29
Health technician	0.4417	19	14.025	18	18.6	30
Construction	0.4077	20	11.451	38	22.721	10
Mechanic	0.405	21	12.215	34	18.553	31
Other precision craft	0.3848	22	12.381	32	22.286	11
Protective service	0.3831	23	13.52	23	14.64	38
Computer operator	0.3593	24	14.191	17	21.809	15
Secretary	0.3406	25	13.695	20	26.373	2
Other sales	0.3385	26	15.358	10	21.395	19
Forestry/fishing	0.3232	27	11.402	39	22.065	13
Records	0.3231	28	13.733	19	19.88	24
Other transportation	0.2913	29	13.158	25	21.655	16
Other administrative	0.2901	30	13.148	26	21.579	17
Machine operator	0.2635	31	11.363	40	23.492	7
Assembler	0.2564	32	11.908	35	19.288	26
Vehicle operator	0.2552	33	12.33	33	25.4	4
Health service	0.2543	34	12.939	28	13.521	39
Retail sales	0.2484	35	12.677	31	13.034	40
Personal service	0.2431	36	13.677	21	24.273	6
Farm laborer	0.2329	37	10.618	43	18.099	32
Construction labor	0.208	38	10.76	42	17.602	35
Mail distribution	0.2031	39	12.704	30	25.654	3
Food service	0.203	40	11.623	36	11.545	42
Other laborer	0.1944	41	11.089	41	17.926	33
Building service	0.1928	42	11.463	37	24.315	5
Handlers	0.1803	43	13.135	27	15.509	37

TABLE 3. Comparison of 1997 NCS and 2001 CPS wage estimations with only human capital controls

	CPS	NCS
HS grad	.297***	
Some college	.468***	
College grad	.835***	
Advanced degree	1.10***	
Potential experience	.035***	
Potential experience^2	-.001***	
Knowledge = 2		.280***
		(.003)
Knowledge = 3		.554***
		(.003)
Knowledge = 4		.843***
		(.003)
Knowledge = 5		.954***
		(.004)
Knowledge = 6		1.16***
		(.003)
Knowledge = 7		1.50***
		(.004)
Knowledge = 8		1.93***
		(.007)
Knowledge = 9		2.10***
		(.031)
R-squared	.222	.693
No. obs.	64,924	135,408

TABLE 4. Effect of controlling for occupation in NCS wage estimation

	1	2
Knowledge = 2	.227	.179
Knowledge = 3	.467	.369
Knowledge = 4	.731	.589
Knowledge = 5	.883	.783
Knowledge = 6	1.08	.995
Knowledge = 7	1.43	1.30
Knowledge = 8	1.86	1.69
Knowledge = 9	2.03	1.89
Part-time job	-.164	-.087
Incentive pay	.212	.174
Unionized	-.066	-.033
Non-profit estab.	.169	.166
Ln(estab. size)	.022	.023
Located in northeast	.011	.005
Located in midwest	-.010	-.026
Located in south	-.059	-.079
Controls for occupation?	NO	Yes
R-squared	.747	.807
No. obs.	135,408	135,408

NOTES: Due to the large sample size, standard errors are very small and are not reported here.

TABLE 5. Effect of adding skills to wage estimation on explanatory power of model

	Adjusted R-squared
Knowledge	.747
Including supervision received	.764
Including guidelines	.768
Including complexity	.763
Including scope and effect	.762
Including personal contacts	.749
Including purpose of contacts	.748
Including physical demands	.747
Including work environment	.748
Including supervisory duties	.749
Including all skills simultaneously	.779
Including all skills plus % female and % minority	.784
Including all skills and occupation indicators	.824
Including occupation indicators	.807

NOTES: Each line represents the adjusted R-squared from a wage estimation that includes all variables listed in TABLE 4 plus the human capital control indicated.

TABLE 6. Moments of the distribution of within-occupation average wage residuals for various sets of human capital controls

	Mean	Standard Dev.	Skewness	Kurtosis
Knowledge alone	.0280	.1532	-.9349	14.16
Including occupation indicators	2.74e-11	9.97e-10	-.0516	8.61
Including supervision received	.0246	.1434	-1.00	18.17
Including guidelines	.0195	.1366	-.7194	17.33
Including complexity	.0190	.1445	-1.438	21.40
Including scope and effect	.0188	.1406	-1.402	18.86
Including personal contacts	.0253	.1513	-.8431	14.66
Including purpose of contacts	.0302	.1545	-.8568	14.02
Including physical demands	.0277	.1531	-.9514	14.26
Including work environment	.0241	.1504	-1.14	15.61
Including supervisory duties	.0311	.1532	-.9129	13.94
Including all skill requirements	.0151	.1361	-1.321	23.20
Including all skills plus % female and % minority	.0012	.1345	-1.54	25.26

NOTES: Each line results from a separate wage estimation including all variables listed in TABLE 4 plus the human capital control indicated. Residuals were collected and then averaged within each of 468 separate 3-digit occupations.

TABLE 7. Breusch-Pagan tests of whether job skills are a source of heteroskedasticity in NCS (CPS) wage estimations that control for knowledge (human capital) and occupation

	NCS	CPS
Knowledge	--	11.41***
Supervision rec'd	1,500***	2.72*
Guidelines	1,216***	0.18
Complexity	1,289***	3.77**
Scope and effect	1,562***	0.00
Personal contacts	2,207***	147.5***
Purpose of contacts	2,226***	162.2***
Physical demands	163***	33.2***
Work environment	429***	214.1***
Supervisory duties	1,456***	126.4***
All factors	3,964***	863.4***

NOTES: Breusch-Pagan test of heteroskedasticity related to skill indicated. For NCS, this tests individual wage residuals with individual reported skill level. For CPS, this tests individual wage residuals with occupation-specific median skill level. * indicates p<.10, ** indicates p<.05, *** indicates p<.01.

FIGURE 1. CPS (NCS) Wage Residuals by Occupation with Human Capital (Knowledge) Controls

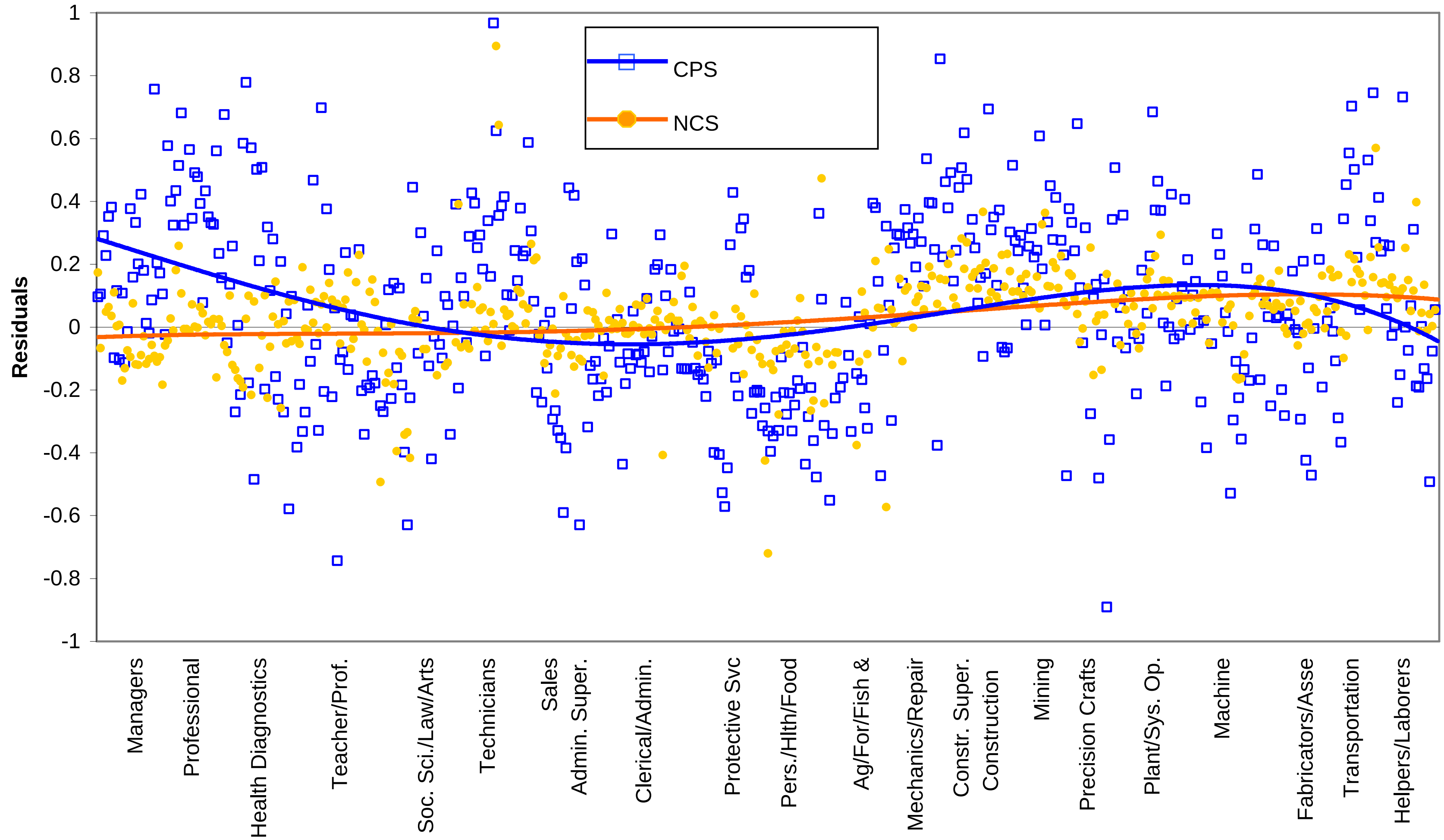

FIGURE 2. Effect on Residuals of Adding Occupation Indicators to Wage Regression

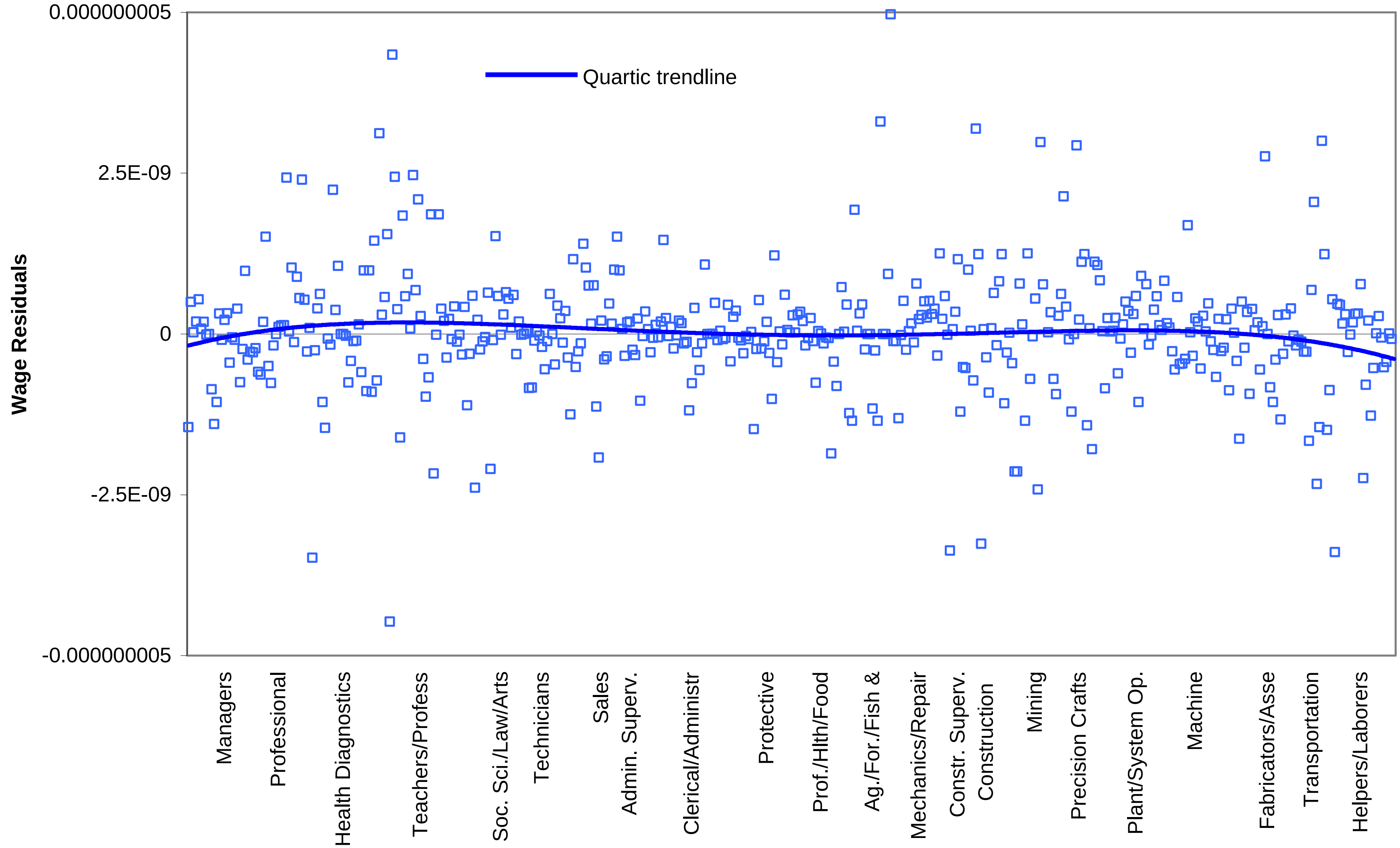

FIGURE 3A. Supervision Received by Occupation (with quartic trendline)

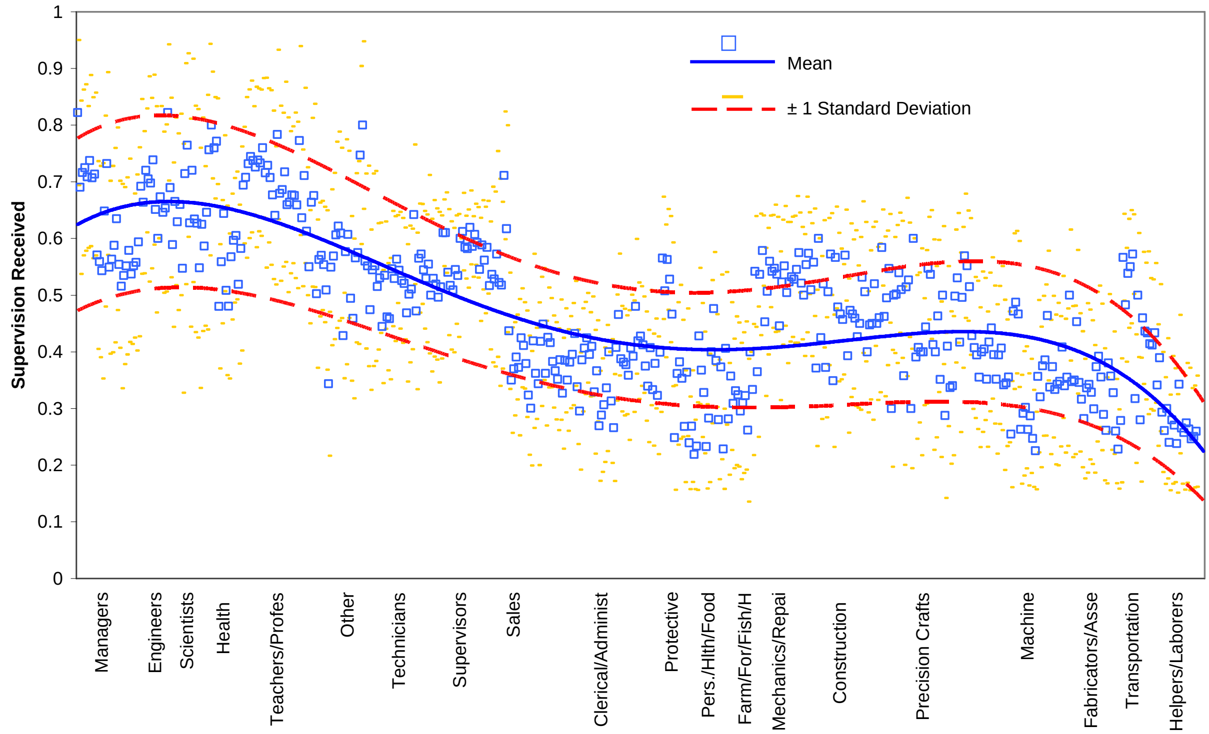

Figure 3B. Guidelines by Occupation (withquartic trendline)

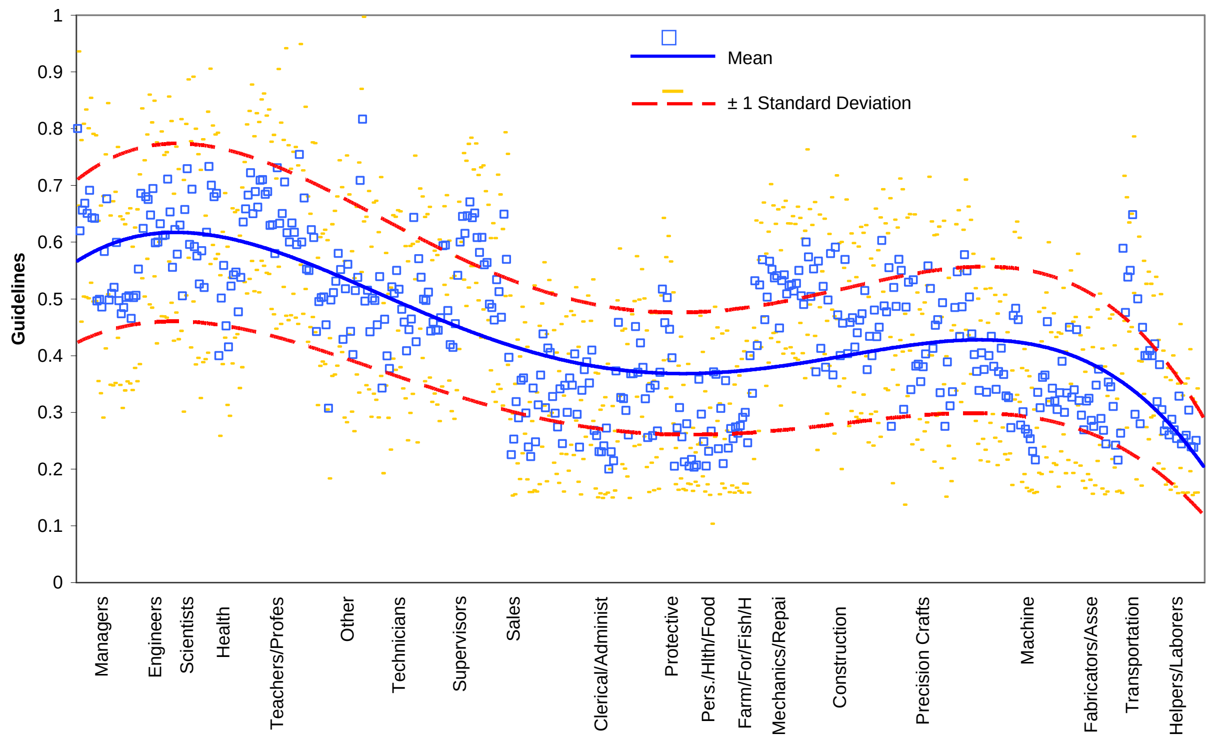

FIGURE 3C. Complexity by Occupation (with quartic trendline)

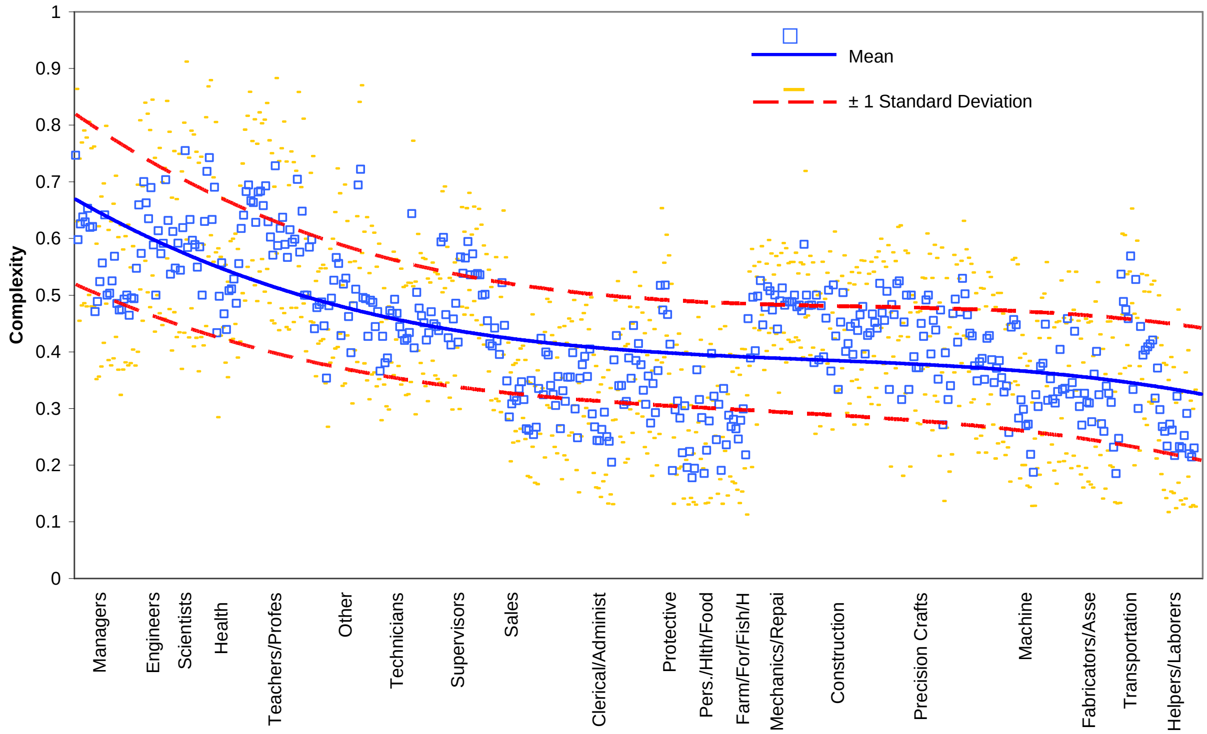

FIGURE 3D. Scope and Effect by Occupation (with quartic trendline)

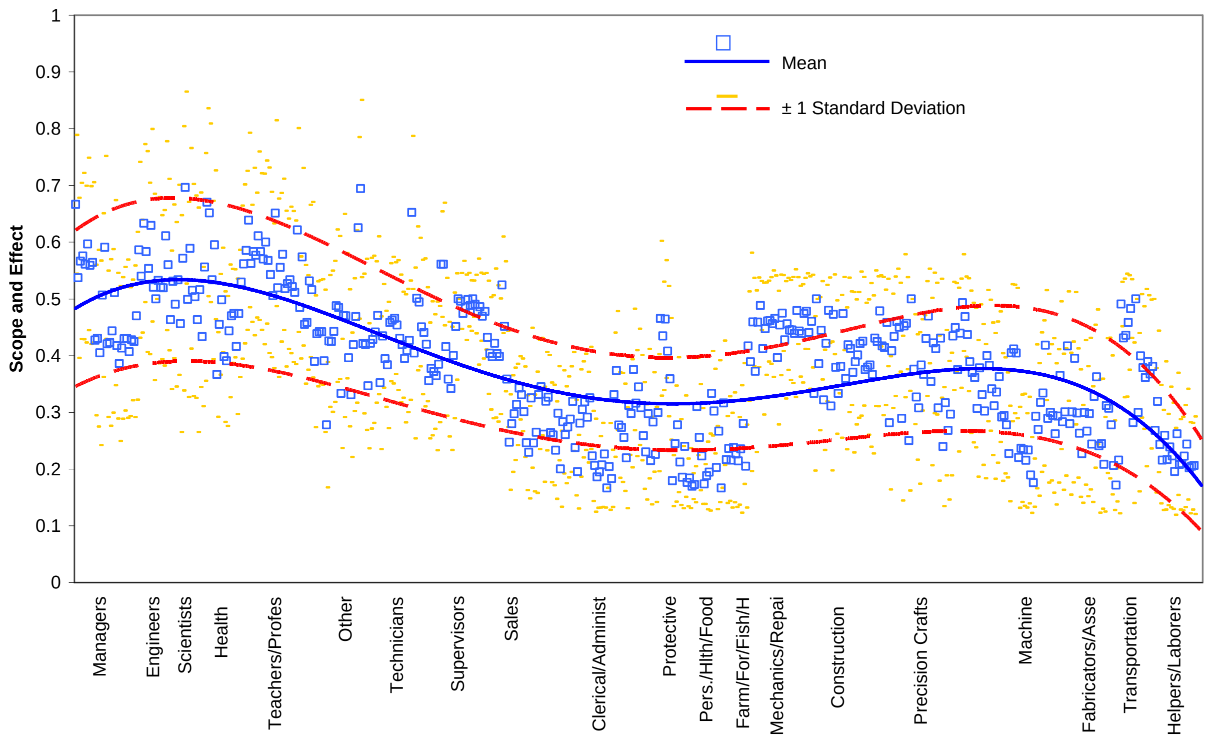

FIGURE 3E. Personal Contacts by Occupation (with quartic trendline)

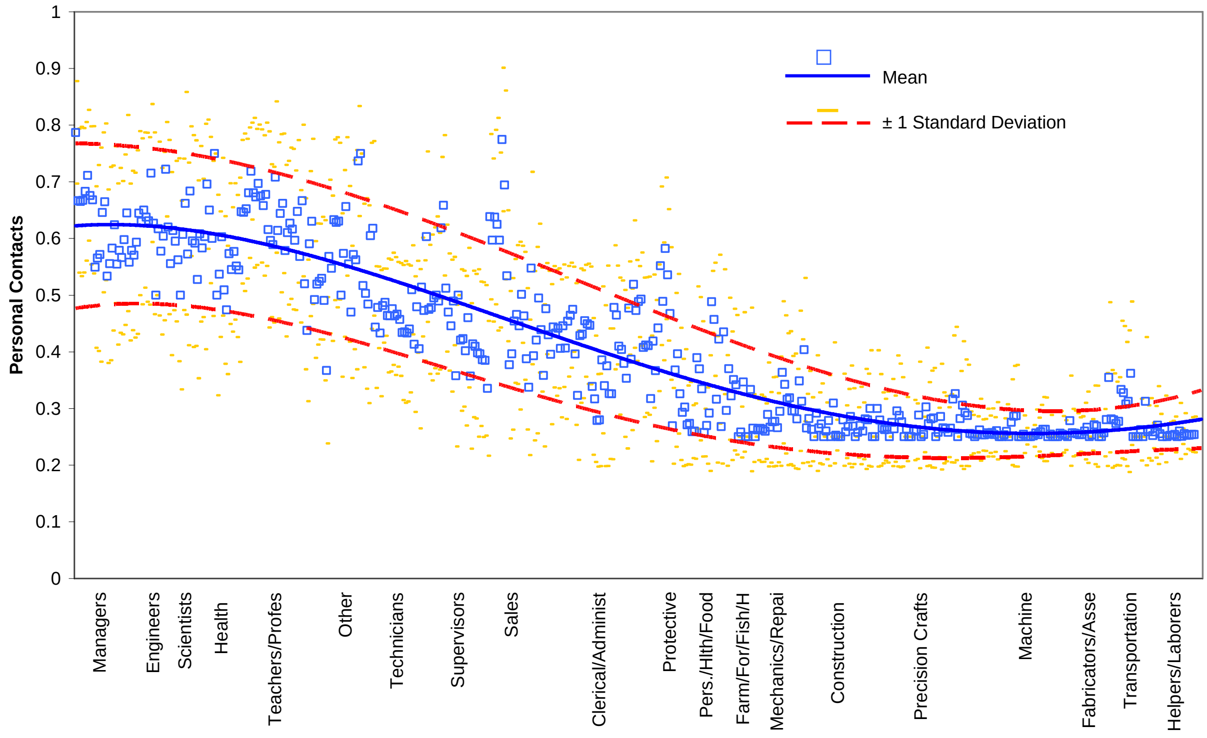

FIGURE 3F. Purpose of Contacts by Occupation (with quartic trendline)

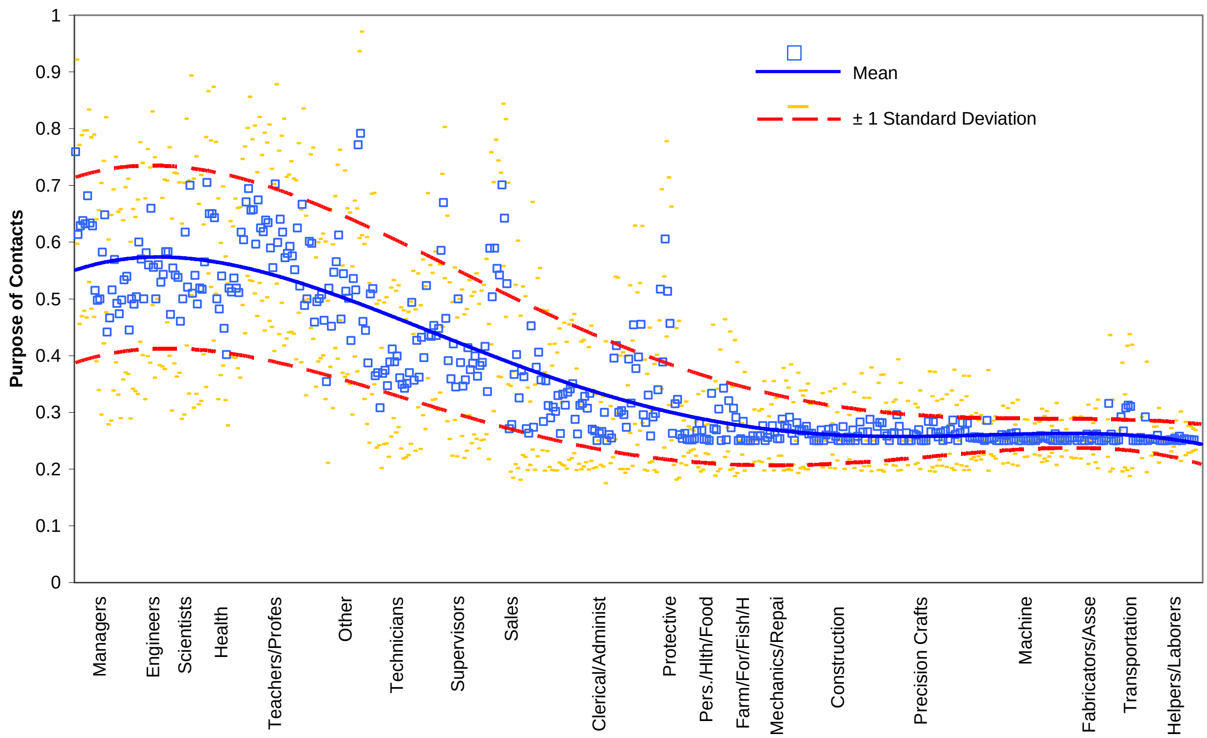

FIGURE 3G. Physical Demands by Occupation (with quartic trendline)

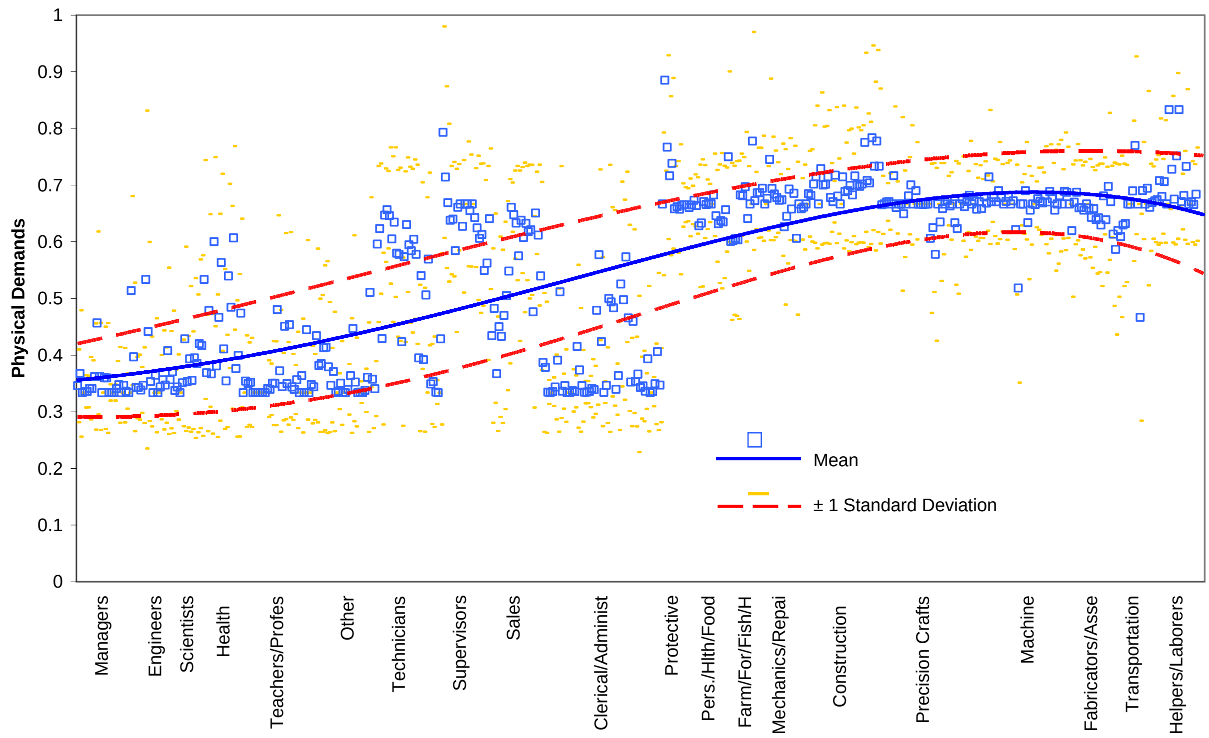

FIGURE 3H. Work Environment by Occupation (with quartic trendline)

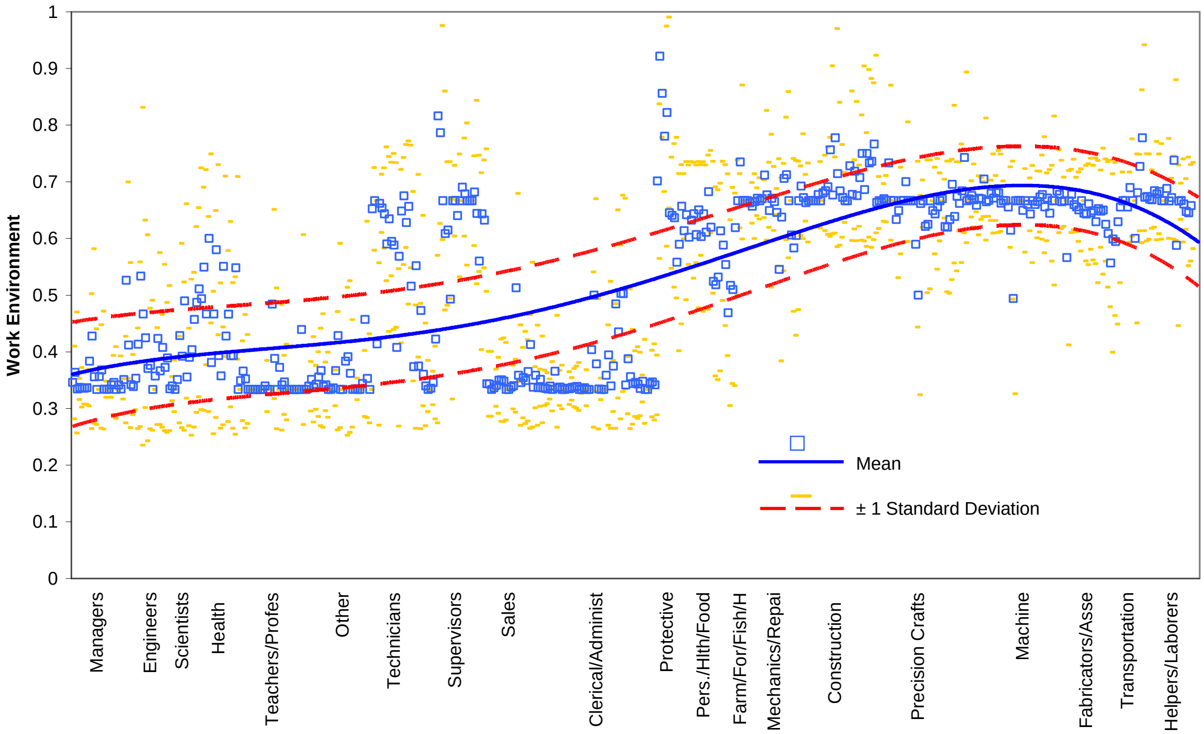

FIGURE 3I. Supervisory Duties by Occupation (with quartic trendline)