Occupational Distance and Pairwise Earnings Correlation

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Abstract: This paper measures intertemporal earnings correlation across occupations in the U.S. using the Current Population Survey, 1971-2012. Then predictors of occupational earnings correlation are identified from among measures of occupational dissimilarity based on the O*Net database. Its findings consist of several surprisingly positive and U-shaped relationships between distance measures and measures of earnings correlation, as well as distance measures with negative estimated effects on earnings correlation. The explanatory power of distance measures for earnings correlations is weak, however, rejecting the simple theory of spatially dependent sectoral shifts among occupations.
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1. Introduction

Evidence that the specificity of human capital follows occupational lines has been accumulating in the forms of returns to occupational tenure (Kambourov and Manovskii, Occupational Specificity of Human Capital 2009), earnings penalties associated with "skill switching" by displaced workers (Poletaev and Robinson 2008), and the pattern of occupational mobility (Gathmann and Schönberg 2010). This confirms what is widely assumed: that occupations are a basis for differentiation among labor market, with boundaries drawn either by an official taxonomy or according to requisite human capital common to multiple occupations. Even if each occupation requires a unique set of human capital, some pairs' (of occupations) requirements overlap more than other pairs. This prompts the question of how the wages in each occupation relate to each other. Specifically, do occupations with more similar human capital requirements have earnings that more consistently move together? This paper identifies which occupations' earnings move together over time and to what degree co-movement can be explained by measures of occupational dissimilarity (distance).

There are several reasons one would wish to know about the co-movement of wages across occupations. In addition to the value of that knowledge for studies of business cycles, it would also help workers assemble a portfolio of human capital that would help them smooth economic shocks (e.g., by maintaining skills useful in occupations that covary negatively with one another), or individuals to find a spouse equipped to reduce fluctuations in household income. However surprisingly little analysis has been performed to uncover determinants of intertemporal earnings correlation across occupations. This paper fills that void by combining two sets of statistics that are both interesting in their own right: a catalog of the correlations between occupations' (log of average annual) earnings using data from the last several decades in the U.S. and the corresponding distance measures based on occupational attributes.

In the tradition of the aforementioned authors, I use measures of dissimilarity between pairs of occupations to expose predictors of occupational earnings correlation. Specifically the measures I employ are distances between each pair of occupations' O*Net (O*Net 2011) measures. These measures capture how different the requisite human capital and tasks performed are between two occupations. The hypothesis is that pairs of occupations that are different, in terms of distance measures constructed from the O*Net, have less correlated earnings because they have fewer skills in common and, hence, weaker dependence between their demand shifts. I find modest support for this hypothesis. Several distance measures reveal a statistically significant relationship with the earnings correlation measures, however their overall explanatory power is weak.

The remainder of the paper is organized as follows. Section 2 provides an overview of the theoretical bases for occupational earnings correlation and the current state of this analysis heretofore. Section 3 summarizes the data and methods used in the present analysis. Section 4 summarizes the results, and Section 5 discusses their interpretation and concludes.

2. Background and Literature Review

The closest antecedent to this paper is Conley and Dupor's (2003) analysis of industry-specific productivity growth. Their research is a natural point of departure for two reasons. First it contains a simple framework for modeling how sectors' productivity growth rates co-move. Second Conley and Dupor (C&D) utilize distance measures based on each pair of industries' input vectors, i.e., the shares of input costs paid to the other sectors. Methods used in this paper are similar to those in C&D section 4.1, in which the covariance between sectoral productivity shocks is a function of the distance measures between sectors (340-42). A salient difference between this paper and theirs is the use of occupations as the unit of analysis instead of industries.

C&D examine the consequences of stochastic technological progress in multiple sectors that grow at different rates, which dates back to Lucas and Prescott (1974), was elaborated upon by Lilien (1982), and creates “sectoral shifts” in labor markets. The shocks originate either in output demand and affect derived labor demand or in the sector’s production technology directly. In either case, the consequence is sector-specific demand fluctuations and wage differentials. In a frictionless labor market, reallocation by workers would then compete away the differentials, resulting in two wage movements: up with sectoral shocks and down with entry. Sectors with co-varying wages, then, would be the consequence of contemporaneous shocks and responses. In this paper I address both main sources of contemporaneous shocks to occupations’ wages. I measure how different each pair of occupations’ industry allocations are; this measures the degree to which they receive common derived demand shocks. And I measure how different their human capital requirements are. This measures the extent to which they have common underlying skill content—the productive inputs that their employers are renting from them.

The values of underlying skills, then, ultimately determine wages, e.g., the popular idea (explained eloquently by Welch (1969)) that earnings are a sum of the products of the worker’s skill endowments and the prices of the skills. When technology changes such that demand for a skill increases, its price changes along with the earnings of all occupations that require the skill. Thus correlation among several occupations’ demand shocks, à la C&D (328-29), reflects the degree to which their skill contents overlap. Several complications ought to be pointed out, though.

The responses to sectoral wage differentials need not be a textbook supply shift. Reder (1955) identified two channels through which sectoral shifts occur: bidding up wages to attract employees and relaxation of hiring standards. Both accomplish the shift, but they have opposing implications for wages, with the latter downgrading the composition of the occupation as an alternative to raising its wages. Which channel predominates depends on the extent to which workers of different skill levels are substitutable (more substitutable implying more down-grading). This spawned a significant literature on cyclical upgrading, of which McLaughlin and Bils (2001) provide a modern example.

Helwege (1992) explores the source of friction in responses to demand shifts, attempting to explain the durability of industry wage differentials. She finds evidence that wage differentials persist because of persistent variation in human capital across industries. The alternative theory, for which she finds no evidence, is that inter-industry differentials are only eroded by young workers entering high-paying industries and accumulating the necessary training, i.e., hiring standards are relaxed in response to the shift, and wages increase after a (training) lag. This could obscure correlation in earnings as a measure of sectoral shocks if training takes longer in different sectors. On the subject of occupational choice, though, Boskin (1974) found evidence that workers do pick occupations in this fashion, i.e., in pursuit of the highest present discounted value of expected net earnings. Moreover occupational mobility work by Kambourov and Manovskii (2009, a) finds that occupation-specific human capital is a significant source of both internal wage dispersion and trans-occupational friction.

Finally sectors need not price skills uniformly. This is a consequence of the impossibility of un-bundling a worker's skills and selling them separately to the highest bidders, demonstrated by Heckman and Scheinkman (1987). Accordingly a technology shock for a particular skill could induce a demand shift within some, but not all, of the occupations that require the skill.

Given a measure of dissimilarity for the human capital of two occupations, it is still reasonable that the demand shifts for the occupations should be related to how distinct their requisites of human capital are. This recommends applying C&D type analysis to occupational earnings correlation. For reasons outlined above, however, distance need not predict less correlation in earnings universally. Indeed some of the findings show greater distance predicting *more* correlated earnings, as well as several U-shaped relationships between distance and earnings correlation.

3. Data and Methods

A. Data

Most of the data come from two sources: the O*Net content model and the March Current Population Survey (CPS). The calculated correlation coefficients are based on yearly observations of the average real earnings in each occupation, classified by the 1990 Census taxonomy (used to compare occupations over many years in the CPS). The sample used is 1971 to 2012 inclusive, i.e., it extends back to when the 1970 Census taxonomy for occupations was first used. Earlier classifications do not translate sufficiently well into the uniform classification scheme used by the IPUMS CPS (King, et al. 2012) database, and inclusion of earlier years results in significant swaths of missing observations. The Integrated Public use Microdata Series (IPUMS) uses a taxonomy for occupations called "OCC1990"—which is a minor revision of the

1990 Census taxonomy—and this makes occupations observed between 1971 and 2012 uniformly classifiable. There are 386 occupations with time series observations spanning these years. Thus there are 74,691 unique correlations possible: 386 “own” correlations and 74,305 “cross” correlations.

Distances in terms of occupational attributes are the hypothesized regressors that explain earnings correlation. The regressors measure dissimilarity between two occupations in terms of the level at which workers must exhibit a given skill or perform a task. The data on occupational distance comes from the O*Net Content Model: “The O*NET database contains several hundred variables that represent descriptors of work and worker characteristics, including skill requirements.” (O*Net). The *activities*, *abilities*, *knowledge* and *skills* files contain the variables to measure distance between occupations, and a summary of these is available on the web site.[1] The version (16.0) database from O*Net consists of scores, from worker and occupational experts questionnaires, assessing the relevance of the various activities, abilities, knowledge, and skills to each occupation.[2]

Relevance is measured on two (ordinal) scales for each occupational dimension: *importance* (1 to 5) and *level* (0 to 7). The importance scale is accompanied by typical language, such as “not important and “extremely important”. The level scale is accompanied by “anchors” that communicate what constitutes a minimal level of performance and what constitutes a sophisticated level. For example, the anchors for ability code, “1.A.2.b.2: Multi-limb Coordination” are shown below.

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[1] http://www.onetcenter.org/dl_files/ContentModel_Detailed.pdf.

[2] “An occupation expert is a person who has several years of experience and training in an occupation. He or she has the expert knowledge required to respond to questions about the skills, knowledge and activities required for work in the occupation” (https://onet.rti.org/faq_oe.cfm#Q5).

Level 2: "Row a boat"

Level 4: "Operate a forklift truck in a warehouse"

Level 6: "Play the drum set in a jazz band"

The ordinal and subjective nature of the data poses an empirical problem: an average of the scores among respondents from an occupation is meaningless except in comparison to averages among that occupation on other dimensions—or to other occupations' averages on the same dimension. A couple features of the scores ameliorate this problem, however.

1. A dimension that the average respondent in an occupation scores higher than another dimension can be regarded as more important (at a more sophisticated level) to the occupation.
2. An occupation in which the average respondent scores a dimension higher than the average respondent from another occupation can be regarded as more important to the occupation with the higher average score.

Together these features—along with a ranking of each occupation on each dimension—make it possible to compare a pair of occupations according to their places in the distributions of the various O*Net dimensions. When constructing multi-dimensional measures, the importance scales can also be used as weights to emphasize only dimensions that are important to both occupations.

There are 377 occupation categories for which earnings and distances are observed. Therefore there are 9 occupations for which correlations are observed but not distances. This is because occupational attributes for those occupations are not reported by the O*Net.[3] Given the

[3] The 9 occupations are: "Legislators", "Professionals not elsewhere classified", "Office machine operators not elsewhere classified", "Other telecom operators", "Mechanics and repairers not elsewhere classified", "Sheet metal duct installers", "Machine operators not elsewhere classified", "Military", and "Unknown".

list of these occupations and their vague definitions, the occupational measures would be so imprecise that they would be quite uninformative. Excluding them from the analysis seems appropriate and does not harm sample size much: reducing it to 70,876 ($\frac{377*376}{2}$) observations.

Finally there are two demand-side reasons for wages to move together: synchronized productivity growth and synchronized output demand shocks. The O*Net measures address the former but not the latter. To overcome this, I measure how different each pair of occupations' industry allocations are, using employer survey data available from the BLS (OES Occupational Data 2010). If the shares of two occupations' employment across industries is identical, e.g., 5% of each is in Construction, 10% of each is in Transportation, they are measured zero units away from one another. Two such occupations would experience derived demand shocks, originating from output demand shocks, in tandem. To distinguish this sort of distance from occupational content distance—which more likely reflects contrasting human capital—I employ two measures of industry employment distance. One is based on the share of employment in the industry, and the other is based on the share in the occupation. Their calculation follows the Euclidean formula used to calculate occupational content distances.

{Table 1 about here}

B. Earnings Correlation Methods

As the dependent variable, I use the correlation coefficient of the earnings for each pair of occupations, indexed by *i* and *j*. These originate from longitudinal observations of the natural logarithm of average annual real earnings (by occupation). Each pair of occupations' time series of earnings is used to calculate the correlation of their averages over time. Additionally I perform a decomposition of the correlation that enables me to measure the portion that stems from similar time trends separately from the portion stemming from correlated residuals.

The logs of average earnings are assumed to have components that are occupation-specific (α_i), year-specific (α_t), trend idiosyncratically over time, and have stochastic fluctuations around their trends (ε_{it}).

$$(1)\ w_{it} = \alpha_i + \alpha_t + \beta_i t + \varepsilon_{it},$$

$$\text{such that } \varepsilon_{it} \sim N(0, \sigma_\varepsilon^2).$$

An occupation's time series sample mean and the cross-sectional sample mean, respectively, $\overline{w}_i$ and $\overline{w}_t$, estimate the expectations, $\mu_i \equiv E^t(w_{it})$, and $\mu_t \equiv E^i(w_{it})$, respectively. Expressing earnings as the deviation from the cross-sectional mean ($\widetilde{w}_{it} \equiv w_{it} - \overline{w}_t$) negates year-specific effects. And expressing $\widetilde{w}$ as a deviation ("$\dot{w}_{it}$") from its time series mean is the basis for the measured correlation (see appendix).

$$(2)\ \sigma_{ij} \equiv E^t\left[\dot{w}_{it}\dot{w}_{jt}\right] = \dot{b}_i\dot{b}_j\sigma_t^2 + Cov\left(\varepsilon_{it}, \varepsilon_{jt}\right) \text{ and,}$$

$$(3)\ \rho_{ij} \equiv Corr\left(\dot{w}_{it}, \dot{w}_{jt}\right) = \frac{\sigma_{ij}}{\left[\sigma_i^2\sigma_j^2\right]^{\frac{1}{2}}}$$

$$\text{where, } \sigma_i^2 \equiv \text{occupation i's intertemporal variance} = E^t(\dot{w}_{it})^2, \text{ and}$$

$$\dot{b}_i \equiv \beta_i - E^i(\beta_i).$$

I calculate for each pair of occupations the sample estimate (r_{ij}) of ρ_{ij} and its components in (2), which enables me to estimate the determinants of each portion separately.

{Table 1: Summary statistics table about here}.

There is a reason to interpret un-weighted results from this exercise with caution. The data themselves are sample means, i.e., they are calculated from CPS micro data. Consequently a pair of occupations with a large representation in the CPS and a precisely measured w_{it} is weighted the same as a pair with a noisy measurement of w_{it}. Appropriate weighting of the observations in the earnings correlation model should improve the precision of its estimates. So I calculate correlation coefficients in which the observations of average earnings are weighted by the inverse of the standard error.

Technically r is a limited dependent variable because it takes values only on the interval [-1, 1]. Therefore it is questionable whether OLS is appropriate. As a robustness check, I estimate a logistic-transformed version of equation 5 (below) but present OLS in this paper for transparency and ease of interpretation.[4] The relationship between earnings correlation and occupational distance is not materially different, but the model fits better using the transformed LHS variable.

C. Explanatory Variables: Distance Measures

The question is which measures of distance predict correlation between two occupations' earnings. I answer this question by regressing the sample correlation coefficients (r_{ij}) on the distance measures using OLS.

$$(5)\ r_{ij} = \alpha + \sum_{m=1}^{161} \gamma_m distance_{mij} + \epsilon_{ij},$$

In (5) *i* and *j* are unique occupation pairs ($i \neq j$), *m* indexes O*Net dimensions in the set of 161 distance measures. I estimate the parameters (γ_m) in (5) with earnings correlation coefficient (or either of the components in (2)) as the dependent variable. Together this set of three estimates reveals whether each occupational distance measure explains: how strongly two occupations'

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[4] The transformation is $logistic(r_{ij}) = \ln\left(\frac{(1+r_{ij})}{(1-\min\{r_{ij},\ 0.999\})}\right)$.

earnings trend together, how strongly their yearly earnings deviations from trend synch up, and how strongly earnings synch up, overall.

The explanatory variables consist of distance measures, indicating how different each pair of occupations is in terms of the O*Net occupational attributes and in terms of their (employment) distributions across industries. They are "distances" in the sense of measuring how far away from one another the occupations are in the rankings of all occupations. Following this premise, I measure the distance between the content of each pair of occupations based on how many ranks away from one another they are on the O*Net scales. For example, there are 41 *activities* dimensions (with an importance and a level scale for each). In total 161 such measures are possible using the *abilities*, *activities*, *knowledge*, and *skills* files. The (square of the) distance measure on dimension *k* for occupations *i* and *j* would be:

$$(6)\ \ distance_{mij} \equiv \left(A_{im} - A_{jm}\right)^2,$$

where A_{im} is the level score for occupation i on dimension m.

Since interpreting 161 coefficients individually is a challenge, I also calculate four multi-dimensional distances based on each of four O*Net files: abilities, activities, skills, knowledge. For example, the distance between two occupations' knowledge vectors would be,

$$(7)\ distance_{knowledge,ij} = \left(\sum_{k=1}^{33} imp_{ik} * imp_{jk} * distance_{kij}\right)^{\frac{1}{2}}.$$

The multi-dimensional distance calculation sums over all the dimensions in one file and weights each dimension according to the relative importance in the two occupations.

$$(8)\ imp_{ik} \equiv \left(\sum_{k=1}^{33} B_{ik}\right)^{-1} B_{ik},$$

where B_{ik} is the importance score for occupation i on dimension k.

4. Results

A. Earnings Correlation Estimates

A histogram for the time series earnings correlations is shown in figure 1.

{Figure 1 about here}

Given the decomposition in equation (2), the explanatory factors for the (similarity in) time trends can be estimated separately from the explanatory factors for overall earnings correlation. The distribution of the former is summarized in figure 2, and the distribution of the second component is shown in figure 3. One fact worth noting is that where the correlation coefficients are bound by the interval [-1, 1], the two components are not, and though there are some that fall outside the interval, such cases are rare.

{Figures 2 & 3 about here}

Since the number of unique correlations is large, the full set of estimates is hard to summarize concisely without narrowing the focus to a small number of occupations. The full data set is available in an online “appendix”, however, for the interested reader. Additionally the regression model in this paper is a novel attempt at making sense of this long list of correlation coefficients. The pertinent question to be answered is, “what kind of occupation pairs have correlated wages?”

B. Earnings Correlation Model

After matching the earnings correlation coefficients for occupation pairs to the corresponding distance measures, I estimate the earnings correlation model (5). The estimated coefficients and standard errors are presented on table A1 in the appendix (first column uses the log of the transformed r_{ij}) for the earnings correlation model. Estimates are also presented in the third column for the distance measures' effects on the time trend component of correlation. And the fourth column shows the distance measures' effects on the residuals' component of correlation. A lot of the distances have coefficients that are statistically significant; this is true of all three dependent variables. For all three, the split between positive and negative is about equal. Roughly one half of the distances have coefficients that are the same-sign for both components (columns 3 and 4); among these same-signed coefficients, the split is again roughly equal between positive and negative. Despite numerous significant relationships between distance and measures of earnings correlation, the explanatory power of the model is weak, especially for the residuals component. This is revealed by low R^2 statistics in all four columns.

To graphically summarize these results, I present a scatterplot of the coefficients from the "trends" regression against the coefficients from the "residuals" regression. This illustrates which dimensions of occupational distance contribute most to earnings correlation and through which part of the decomposition they do so. The plots are divided into four groups, based on the O*Net file in which each is found. Finally the plots are restricted to include only variables with at least one *t* statistic greater than 3 in absolute value. This makes the graphs easier to read by excluding variables with imprecise coefficient estimates.

{Figure 4 about here }

The multi-dimensional distance measures allow for an easier interpretation of how dissimilarity relates to earnings correlation. They also reveal interesting non-monotonic relationships. Table 2 presents the results of regressing earnings correlation on the four multi-dimensional distances and quadratics of those distances. All four have statistically significantly non-monotonic relationships, with Abilities and Activities being the largest in magnitude. Along with Knowledge, these three have U-shaped relationships with earnings correlation. Distance between occupations initially means less correlation, but then a minimum is reached and far away occupations' earnings become *more* correlated with distance. Skills-related distance has the opposite shape (concave), reaching a maximum in the irrelevant (negative) range; therefore it is monotonically decreasing on the positive interval. But it is the weakest predictor of the four.

{Table 2 about here}

The industry distribution distance based on occupation employment shares exhibits a U-shaped relationship with earnings correlation, however, the minimum occurs in the negative range, so its earnings correlation is monotonically increasing in this distance (over the positive range). The analogous measure based on the shares of industry employment exhibits an inverted U-shape, and is decreasing over the positive range. This is the least surprising finding: two sets of industry shares that are different from one another means the two occupations' earnings are less correlated.

{Table 3 about here}

5. Discussion and Conclusions

So far this research has been exploratory in nature. I have not tested an explicit theoretical prediction of which distance measures should explain earnings correlation and why. Generally my expectation is that dissimilarity makes two occupations' earnings less positively correlated, but it seems unlikely to make them more *negatively* correlated. This suggests, though, that a non-monotonic relationship may exist, and indeed I find evidence of that using multi-dimensional distances. Distances based on occupational abilities, activities, and knowledge exhibit a U-shaped relationship with earnings correlation. This finding is novel compared to C&D's finding of monotonicity among industries: ". . . covariance patterns . . . appear dictated by [input-based] distances . . . covariance declines as [input-based] distances grow." (Conley and Dupor 2003).

If occupations' labor markets mimicked C&D's (2003) spatially correlated industries, pairs of occupations would experience common demand shifts owing to productivity changes that affect the human capital general to both occupations. Then the more overlapping are their human capital requirements, the more correlation in demand shifts for the two occupations. My finding of a U-shaped relationship between earnings correlation and distance suggests that overlapping human capital requirements is not the whole story. It is tempting to conclude that the non-monotonicity reflects non-redundant and therefore complementary human capital embodied in far distant occupations. Accordingly a productivity increase for one would affect the demand for both occupations. This conclusion, however, downplays the complexity of supply responses discussed in Section 2. Especially since the explanatory power of the model is small, it is dubious that occupations experience frictionless spatially dependent sectoral shifts. Consequently I am reluctant to endorse the interpretation that the findings signal productive complementarity without qualification.

There are other reasons to interpret these findings with care. First there is employees' expectations of the intertemporal earnings profile in each occupation, i.e., climbing or declining. This idea stems from Helwege's (1992) paper, in which she reminds us that new entrants will require (pay) a premium to enter sectors with anticipated declining (climbing) future earnings. That paper is about industries, but the reasoning applies to occupations: more similarity between a pair of them suggests similar anticipated earnings streams. It is clear neither how efficient employees' expectations are nor to what extent they can act on predictable (a priori) earnings trends, but it's just one more possible source of wage differentials to obscure the effects of sectoral shifts.

With those caveats in mind, though, there are several useful lessons from the findings. I have identified occupational attributes on which dissimilarity predicts less earnings correlation. This is informative for employees who would like to diversify their human capital, e.g., if one's present résumé demonstrates only a modest degree of "Social Perceptiveness," he has an incentive to invest in this skill because occupations that require it tend to be "countercyclical" to those that do not (his present occupation).[5]

Another significant application for these results is marital stability. Risk-sharing theories of marriage (Weiss 1997) imply that household earnings risks can be reduced by diversifying, i.e., spouses choosing jobs with uncorrelated shocks. Measuring correlation between the average incomes of two spouses' occupations help identify the effect of having un-diversified earnings risks on the probability of marital dissolution.[6]

Simply measuring the pairwise correlation between occupations' earnings is an exercise that bears fruit by itself, and several extensions are conceivable. The present paper considers the entire period (1971-2012) to estimate earnings correlation. But this period could be analyzed in separate parts and used to observe changes in the degree of correlation in earnings. Interesting questions about the effects of de-unionization, female labor force participation, and international trade liberalization could be answered by examining earnings correlations based on subsamples of the CPS, e.g., before and after enactment of NAFTA.

[5] Social Perceptiveness: "Being aware of others' reactions and understanding why they react as they do" (O*Net).
[6] Van Kammen and Adams (2013) are working on a paper along these lines.

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Appendix 1: Wage Correlation Decomposition

The de-meaned wages:

$$(A1)\ \widetilde{w}_{it} \equiv w_{it} - \overline{w}_t = \alpha_i - E^i(\alpha_i) + t\left(\beta_i - E^i(\beta_i)\right) + \varepsilon_{it} - 0,$$

are expressed as deviations from their time series expectations:

$$(A2)\ E^t(\widetilde{w}_{it}) = a_i - E^i(a_i) + E^t(t)\left(\beta_i - E^i(\beta_i)\right) + 0;$$

$$(A3)\ \dot{w}_{it} \equiv \widetilde{w}_{it} - E^t(\widetilde{w}_{it}) = \left(t - E^t(t)\right)\left(\beta_i - E^i(\beta_i)\right) + \varepsilon_{it}.$$

Covariance between two occupations (*i* and *j*) is defined:

$$(A4)\ \sigma_{ij} \equiv E^t\left[\dot{w}_{it}\dot{w}_{jt}\right] = E^t\left[\left(\widetilde{w}_{it} - E^t(\widetilde{w}_{it})\right)\ \left(\widetilde{w}_{jt} - E^t\left(\widetilde{w}_{jt}\right)\right)\right].$$

$$(A5)\ \sigma_{ij} = \dot{b}_i\dot{b}_j\sigma_t^2 + Cov\left(\varepsilon_{it}, \varepsilon_{jt}\right) + 0\ + 0, \text{where}$$

$$\dot{b}_i \equiv \beta_i - E^i(\beta_i).$$

The only terms that have a non-zero expectation (in A4) are the first two “diagonals”, which have the interpretations, respectively, of “correlation in time trends” and “correlation in shocks”.

The occupation-specific time trends are estimated from a random trends model. To estimate the occupation-specific trends, I use a method described in Wooldridge (2002). I take the first difference of (1); this negates the fixed effect, “alpha i”, but the trend ($\beta_i t - \beta_i(t-1) = \beta_i$) is now a fixed effect in the differenced model. I then estimate “beta i” using a fixed effects regression of change in average earnings on the transformed year-fixed effects. Using Wooldridge’s notation, these are *xi* subscript t:

$$(4)\ \Delta w_{it} = \xi_t + \beta_i + \Delta\varepsilon_{it},$$

where the deltas represent first differences. The fixed component of the residuals can then be estimated by fitting the model, and these are the occupation-specific time trend estimates.[1] The time trend component of earnings correlation is the product of the two occupations' time trends (expressed as deviations from the mean) times a positive constant reflecting the length of the time series. This component is positive if both occupations' earnings trend faster than average or both trend slower than average and are negative otherwise.

1 This method is equivalent to (cross-sectionally) de-meaning the observations and regressing de-meaned earnings on time.

Table A1: Estimates from regression of earnings correlation on single dimension distances.

Distance Measure	Log of Transformed Earnings Correlation, Occupations i and j	Correlation of Earnings Occupations i and j	Earnings Correlation Originating from Time Trends	Earnings Correlation Originating from Shocks
Arm-Hand Steadiness	0.1878	0.0799	0.0945	-0.0146
	(0.0515)***	(0.0228)***	(0.0253)***	(0.0195)
Auditory Attention	-0.0271	-0.017	0.0083	-0.0252
	(0.0346)	(0.0153)	(0.0170)	(0.0131)*
Category Flexibility	-0.0954	-0.0389	-0.0471	0.0082
	(0.0376)**	(0.0167)**	(0.0184)**	(0.0143)
Control Precision	-0.2214	-0.0942	-0.0557	-0.0385
	(0.0598)***	(0.0265)***	(0.0294)*	(0.0227)*
Deductive Reasoning	-0.2234	-0.1072	-0.1181	0.0109
	(0.0758)***	(0.0336)***	(0.0372)***	(0.0287)
Depth Perception	0.0253	0.0132	0.0138	-0.0006
	(0.0490)	(0.0217)	(0.0240)	(0.0186)
Dynamic Flexibility	0.1586	0.0681	0.0498	0.0182
	(0.0285)***	(0.0126)***	(0.0140)***	(0.0108)*
Dynamic Strength	0.2354	0.1103	0.1119	-0.0016
	(0.0673)***	(0.0299)***	(0.0331)***	(0.0255)
Explosive Strength	-0.1573	-0.0658	-0.0892	0.0234
	(0.0264)***	(0.0117)***	(0.0129)***	(0.0100)**
Extent Flexibility	0.0045	0.0022	-0.0192	0.0215
	(0.0582)	(0.0258)	(0.0286)	(0.0221)
Far Vision	-0.0449	-0.0211	-0.0154	-0.0057
	(0.0253)*	(0.0112)*	(0.0124)	(0.0096)
Finger Dexterity	-0.1841	-0.0836	-0.0825	-0.0011
	(0.0404)***	(0.0179)***	(0.0198)***	(0.0153)
Flexibility of Closure	0.0239	0.0115	-0.0021	0.0136
	(0.0311)	(0.0138)	(0.0152)	(0.0118)
Fluency of Ideas	-0.0313	-0.0196	0.0328	-0.0523
	(0.0696)	(0.0309)	(0.0342)	(0.0264)**
Glare Sensitivity	-0.3457	-0.1445	-0.1485	0.004
	(0.0476)***	(0.0211)***	(0.0234)***	(0.0181)
Gross Body Coordination	-0.0507	-0.0281	-0.0454	0.0173
	(0.0691)	(0.0306)	(0.0339)	(0.0262)
Gross Body Equilibrium	0.086	0.0331	0.0361	-0.0031
	(0.0472)*	(0.0209)	(0.0232)	(0.0179)
Hearing Sensitivity	0.1733	0.0772	0.0634	0.0139

	(0.0370)***	(0.0164)***	(0.0182)***	(0.0141)
Inductive Reasoning	0.4404	0.1946	0.1638	0.0308
	(0.0669)***	(0.0297)***	(0.0329)***	(0.0254)
Information Ordering	0.1181	0.052	0.048	0.0041
	(0.0432)***	(0.0192)***	(0.0212)**	(0.0164)
Manual Dexterity	0.212	0.0969	0.065	0.0319
	(0.0588)***	(0.0261)***	(0.0289)**	(0.0223)
Mathematical Reasoning	-0.1719	-0.0819	-0.0802	-0.0017
	(0.0588)***	(0.0261)***	(0.0289)***	(0.0223)
Memorization	0.0245	0.0096	0.009	0.0006
	(0.0334)	(0.0148)	(0.0164)	(0.0127)
Multilimb Coordination	0.1787	0.0734	0.0877	-0.0143
	(0.0647)***	(0.0287)**	(0.0318)***	(0.0245)
Near Vision	-0.0334	-0.0182	-0.0333	0.0151
	(0.0287)	(0.0127)	(0.0141)**	(0.0109)
Night Vision	0.221	0.0975	0.0853	0.0122
	(0.0536)***	(0.0238)***	(0.0263)***	(0.0203)
Number Facility	-0.0033	0.0019	-0.0228	0.0246
	(0.0527)	(0.0234)	(0.0259)	(0.0200)
Oral Comprehension	-0.2128	-0.0918	-0.0946	0.0028
	(0.0615)***	(0.0273)***	(0.0302)***	(0.0233)
Oral Expression	-0.0884	-0.0498	-0.0201	-0.0297
	(0.0590)	(0.0261)*	(0.0290)	(0.0224)
Originality	-0.0155	0.0044	-0.0231	0.0275
	(0.0658)	(0.0292)	(0.0323)	(0.0250)
Perceptual Speed	0.024	0.01	0.0099	0.0001
	(0.0291)	(0.0129)	(0.0143)	(0.0111)
Peripheral Vision	0.0736	0.0299	0.035	-0.0051
	(0.0591)	(0.0262)	(0.0290)	(0.0224)
Problem Sensitivity	-0.1473	-0.0676	-0.0402	-0.0274
	(0.0454)***	(0.0201)***	(0.0223)*	(0.0172)
Rate Control	-0.0796	-0.0371	-0.0456	0.0085
	(0.0637)	(0.0282)	(0.0313)	(0.0242)
Reaction Time	-0.3516	-0.1564	-0.153	-0.0034
	(0.0745)***	(0.0330)***	(0.0366)***	(0.0283)
Response Orientation	0.3226	0.1334	0.1057	0.0277
	(0.0662)***	(0.0293)***	(0.0325)***	(0.0251)
Selective Attention	0.0658	0.0315	0.029	0.0025
	(0.0273)**	(0.0121)***	(0.0134)**	(0.0104)
Sound Localization	-0.1723	-0.0731	-0.0797	0.0066
	(0.0479)***	(0.0212)***	(0.0235)***	(0.0182)

Spatial Orientation	0.0073	0.0007	0.023	-0.0223
	(0.0439)	(0.0195)	(0.0216)	(0.0167)
Speech Clarity	0.078	0.0375	0.0579	-0.0204
	(0.0472)*	(0.0209)*	(0.0232)**	(0.0179)
Speech Recognition	-0.0358	-0.0158	-0.0552	0.0394
	(0.0411)	(0.0182)	(0.0202)***	(0.0156)**
Speed of Closure	-0.0083	-0.0054	0.0025	-0.0079
	(0.0338)	(0.0150)	(0.0166)	(0.0128)
Speed of Limb Movement	0.0132	0.0079	0.0163	-0.0084
	(0.0470)	(0.0208)	(0.0231)	(0.0178)
Stamina	0.1796	0.0733	0.0956	-0.0222
	(0.0639)***	(0.0283)***	(0.0314)***	(0.0242)
Static Strength	-0.3381	-0.149	-0.1185	-0.0304
	(0.0642)***	(0.0285)***	(0.0315)***	(0.0243)
Time Sharing	0.0538	0.0265	0.024	0.0025
	(0.0247)**	(0.0110)**	(0.0121)**	(0.0094)
Trunk Strength	0.0119	0.0076	0.0112	-0.0036
	(0.0508)	(0.0225)	(0.0250)	(0.0193)
Visual Color Discrimination	0.0503	0.0191	0.0131	0.0059
	(0.0305)*	(0.0135)	(0.0150)	(0.0116)
Visualization	-0.0337	-0.0146	0.0064	-0.021
	(0.0331)	(0.0147)	(0.0163)	(0.0126)*
Wrist-Finger Speed	0.0729	0.0342	0.0342	0
	(0.0377)*	(0.0167)**	(0.0185)*	(0.0143)
Written Comprehension	0.0332	0.0193	0.0166	0.0027
	(0.0739)	(0.0328)	(0.0363)	(0.0281)
Written Expression	-0.1373	-0.0595	-0.0973	0.0378
	(0.0717)*	(0.0318)*	(0.0352)***	(0.0272)
Analyzing Data or Information	-0.2076	-0.0936	-0.0363	-0.0573
	(0.0501)***	(0.0222)***	(0.0246)	(0.0190)***
Assisting and Caring for Others	-0.0147	-0.0075	-0.02	0.0125
	(0.0232)	(0.0103)	(0.0114)*	(0.0088)
Coaching and Developing Others	0.047	0.0201	-0.0099	0.03
	(0.0410)	(0.0182)	(0.0202)	(0.0156)*
Communicating with Persons Outside Organization	0.1163	0.0491	0.0484	0.0007
	(0.0428)***	(0.0190)***	(0.0210)**	(0.0162)

Communicating with Supervisors, Peers, or Subordinates	-0.0009	-0.0032	-0.0171	0.0139
	(0.0391)	(0.0174)	(0.0192)	(0.0148)
Controlling Machines and Processes	-0.0864	-0.0379	-0.0454	0.0075
	(0.0468)*	(0.0207)*	(0.0230)**	(0.0177)
Coordinating the Work and Activities of Others	0.0577	0.0242	0.0218	0.0024
	(0.0387)	(0.0171)	(0.0190)	(0.0147)
Developing Objectives and Strategies	0.1544	0.0681	0.043	0.0251
	(0.0412)***	(0.0183)***	(0.0203)**	(0.0157)
Developing and Building Teams	0.0635	0.0284	0.0436	-0.0151
	(0.0383)*	(0.0170)*	(0.0188)**	(0.0145)
Documenting/Recording Information	-0.0819	-0.0386	-0.043	0.0044
	(0.0357)**	(0.0158)**	(0.0175)**	(0.0136)
Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment	0.0544	0.0241	0.0101	0.014
	(0.0343)	(0.0152)	(0.0169)	(0.0130)
Establishing and Maintaining Interpersonal Relationships	-0.0507	-0.022	-0.0108	-0.0112
	(0.0362)	(0.0161)	(0.0178)	(0.0137)
Estimating the Quantifiable Characteristics of Products, Events, or Information	0.0321	0.0149	0.0145	0.0004
	(0.0287)	(0.0127)	(0.0141)	(0.0109)
Evaluating Information to Determine Compliance with Standards	-0.0449	-0.0186	-0.023	0.0043
	(0.0318)	(0.0141)	(0.0156)	(0.0121)
Getting Information	-0.0703	-0.0306	-0.0432	0.0126
	(0.0383)*	(0.0170)*	(0.0188)**	(0.0145)
Guiding, Directing, and Motivating Subordinates	-0.2295	-0.1078	-0.079	-0.0288
	(0.0409)***	(0.0182)***	(0.0201)***	(0.0155)*

Handling and Moving Objects	-0.1124	-0.0385	-0.0673	0.0287
	(0.0455)**	(0.0202)*	(0.0223)***	(0.0173)*
Identifying Objects, Actions, and Events	-0.0093	-0.0047	-0.006	0.0013
	(0.0311)	(0.0138)	(0.0153)	(0.0118)
Inspecting Equipment, Structures, or Material	-0.09	-0.0458	-0.0609	0.0152
	(0.0369)**	(0.0164)***	(0.0181)***	(0.0140)
Interacting With Computers	0.1244	0.0578	0.0385	0.0193
	(0.0417)***	(0.0185)***	(0.0205)*	(0.0158)
Interpreting the Meaning of Information for Others	-0.1352	-0.0603	-0.0439	-0.0164
	(0.0417)***	(0.0185)***	(0.0205)**	(0.0158)
Judging the Qualities of Things, Services, or People	-0.0257	-0.0113	0.0075	-0.0188
	(0.0300)	(0.0133)	(0.0147)	(0.0114)*
Making Decisions and Solving Problems	0.0121	0.0017	-0.0153	0.017
	(0.0421)	(0.0187)	(0.0207)	(0.0160)
Monitor Processes, Materials, or Surroundings	-0.0603	-0.028	-0.0313	0.0033
	(0.0288)**	(0.0128)**	(0.0142)**	(0.0109)
Monitoring and Controlling Resources	0.0523	0.023	0.0101	0.0129
	(0.0331)	(0.0147)	(0.0163)	(0.0126)
Operating Vehicles, Mechanized Devices, or Equipment	-0.3087	-0.1395	-0.138	-0.0015
	(0.0446)***	(0.0198)***	(0.0219)***	(0.0169)
Organizing, Planning, and Prioritizing Work	0.008	0.0031	0.0052	-0.0021
	(0.0424)	(0.0188)	(0.0208)	(0.0161)
Performing Administrative Activities	-0.137	-0.0617	-0.0358	-0.0259
	(0.0372)***	(0.0165)***	(0.0182)**	(0.0141)*
Performing General Physical Activities	-0.1066	-0.0455	-0.0111	-0.0343
	(0.0512)**	(0.0227)**	(0.0251)	(0.0194)*
Performing for or Working Directly with the Public	0.0178	0.0035	-0.0115	0.015

	(0.0286)	(0.0127)	(0.0140)	(0.0108)
Processing Information	0.0005	-0.0001	-0.0124	0.0123
	(0.0451)	(0.0200)	(0.0221)	(0.0171)
Provide Consultation and Advice to Others	-0.0937	-0.039	-0.0348	-0.0043
	(0.0412)**	(0.0183)**	(0.0203)*	(0.0156)
Repairing and Maintaining Electronic Equipment	-0.1102	-0.0451	-0.0551	0.0101
	(0.0340)***	(0.0151)***	(0.0167)***	(0.0129)
Repairing and Maintaining Mechanical Equipment	0.1024	0.0358	0.0588	-0.023
	(0.0516)**	(0.0229)	(0.0254)**	(0.0196)
Resolving Conflicts and Negotiating with Others	0.0949	0.0445	0.042	0.0026
	(0.0386)**	(0.0171)***	(0.0189)**	(0.0146)
Scheduling Work and Activities	0.1154	0.0511	0.0304	0.0207
	(0.0403)***	(0.0179)***	(0.0198)	(0.0153)
Selling or Influencing Others	-0.0569	-0.0236	-0.0214	-0.0022
	(0.0331)*	(0.0147)	(0.0162)	(0.0126)
Staffing Organizational Units	0.1279	0.0601	0.0346	0.0255
	(0.0337)***	(0.0149)***	(0.0165)**	(0.0128)**
Thinking Creatively	-0.1287	-0.0574	-0.0498	-0.0076
	(0.0384)***	(0.0170)***	(0.0189)***	(0.0146)
Training and Teaching Others	0.0523	0.0279	0.0423	-0.0144
	(0.0370)	(0.0164)*	(0.0182)**	(0.0140)
Updating and Using Relevant Knowledge	0.0961	0.0484	0.0266	0.0218
	(0.0430)**	(0.0191)**	(0.0211)	(0.0163)
Active Learning	0.2815	0.1238	0.1576	-0.0339
	(0.0636)***	(0.0282)***	(0.0312)***	(0.0241)
Active Listening	-0.0496	-0.0225	-0.013	-0.0095
	(0.0652)	(0.0289)	(0.0320)	(0.0247)
Complex Problem Solving	-0.153	-0.0653	-0.0313	-0.034
	(0.0569)***	(0.0252)***	(0.0279)	(0.0216)
Coordination	-0.0163	-0.0071	-0.0278	0.0207
	(0.0362)	(0.0161)	(0.0178)	(0.0137)
Critical Thinking	0.174	0.0806	0.0376	0.043
	(0.0598)***	(0.0265)***	(0.0294)	(0.0227)*
Equipment Maintenance	0.1852	0.0814	0.0808	0.0006

	(0.0618)***	(0.0274)***	(0.0303)***	(0.0234)
Equipment Selection	0.0903	0.0489	0.0577	-0.0088
	(0.0440)**	(0.0195)**	(0.0216)***	(0.0167)
Installation	-0.4675	-0.2083	-0.2084	0.0001
	(0.0302)***	(0.0134)***	(0.0148)***	(0.0115)
Instructing	0.035	0.0147	0.031	-0.0163
	(0.0525)	(0.0233)	(0.0258)	(0.0199)
Judgment and Decision Making	0.0508	0.0249	-0.0103	0.0351
	(0.0591)	(0.0262)	(0.0290)	(0.0224)
Learning Strategies	0.0743	0.0307	0.0446	-0.0139
	(0.0549)	(0.0243)	(0.0270)*	(0.0208)
Management of Financial Resources	-0.0417	-0.0225	-0.0338	0.0113
	(0.0372)	(0.0165)	(0.0183)*	(0.0141)
Management of Material Resources	-0.0181	-0.0059	-0.0014	-0.0045
	(0.0365)	(0.0162)	(0.0179)	(0.0138)
Management of Personnel Resources	0.058	0.0272	0.0197	0.0074
	(0.0461)	(0.0204)	(0.0226)	(0.0175)
Mathematics	0.0624	0.0305	0.0506	-0.0201
	(0.0449)	(0.0199)	(0.0221)**	(0.0171)
Monitoring	-0.1051	-0.042	-0.0615	0.0194
	(0.0458)**	(0.0203)**	(0.0225)***	(0.0174)
Negotiation	0.0615	0.0203	0.0258	-0.0055
	(0.0502)	(0.0222)	(0.0246)	(0.0190)
Operation Monitoring	-0.025	-0.0067	-0.0112	0.0045
	(0.0539)	(0.0239)	(0.0265)	(0.0204)
Operation and Control	0.3522	0.1599	0.1479	0.0121
	(0.0574)***	(0.0255)***	(0.0282)***	(0.0218)
Operations Analysis	-0.0909	-0.0405	-0.0588	0.0183
	(0.0314)***	(0.0139)***	(0.0154)***	(0.0119)
Persuasion	-0.0548	-0.0228	-0.0196	-0.0032
	(0.0497)	(0.0220)	(0.0244)	(0.0189)
Programming	-0.0318	-0.0134	-0.0141	0.0007
	(0.0302)	(0.0134)	(0.0148)	(0.0115)
Quality Control Analysis	0.119	0.0526	0.0356	0.017
	(0.0415)***	(0.0184)***	(0.0204)*	(0.0157)
Reading Comprehension	0.0724	0.0316	0.0031	0.0285
	(0.0742)	(0.0329)	(0.0364)	(0.0281)
Repairing	-0.0736	-0.0383	0.0121	-0.0505

	(0.0621)	(0.0275)	(0.0305)	(0.0235)**
Science	-0.0585	-0.0286	0.0261	-0.0547
	(0.0313)*	(0.0139)**	(0.0154)*	(0.0119)***
Service Orientation	-0.4694	-0.213	-0.2369	0.0238
	(0.0388)***	(0.0172)***	(0.0190)***	(0.0147)
Social Perceptiveness	0.0004	-0.0015	0.0428	-0.0443
	(0.0444)	(0.0197)	(0.0218)**	(0.0168)***
Speaking	0.2083	0.0925	0.0893	0.0032
	(0.0697)***	(0.0309)***	(0.0342)***	(0.0264)
Systems Analysis	0.0141	0.0003	0.0417	-0.0414
	(0.0629)	(0.0279)	(0.0309)	(0.0239)*
Systems Evaluation	0.0892	0.0442	0.012	0.0322
	(0.0654)	(0.0290)	(0.0321)	(0.0248)
Technology Design	0.1519	0.0669	0.0636	0.0034
	(0.0279)***	(0.0124)***	(0.0137)***	(0.0106)
Time Management	-0.0434	-0.018	0.0414	-0.0594
	(0.0480)	(0.0213)	(0.0236)*	(0.0182)***
Troubleshooting	-0.1415	-0.0578	-0.0619	0.004
	(0.0548)***	(0.0243)**	(0.0269)**	(0.0208)
Writing	-0.15	-0.0649	-0.0499	-0.015
	(0.0733)**	(0.0325)**	(0.0360)	(0.0278)
Administration and Management	-0.0492	-0.0233	-0.0348	0.0114
	(0.0361)	(0.0160)	(0.0177)**	(0.0137)
Biology	-0.174	-0.0797	-0.0817	0.002
	(0.0264)***	(0.0117)***	(0.0129)***	(0.0100)
Building and Construction	0.2068	0.0958	0.0912	0.0046
	(0.0294)***	(0.0130)***	(0.0144)***	(0.0112)
Chemistry	0.0341	0.0179	0.0317	-0.0138
	(0.0286)	(0.0127)	(0.0140)**	(0.0109)
Clerical	0.0441	0.0187	0.0101	0.0086
	(0.0349)	(0.0155)	(0.0171)	(0.0132)
Communications and Media	-0.1414	-0.0626	-0.0625	-0.0002
	(0.0390)***	(0.0173)***	(0.0191)***	(0.0148)
Computers and Electronics	0.0425	0.0227	0.0559	-0.0332
	(0.0425)	(0.0188)	(0.0209)***	(0.0161)**
Customer and Personal Service	0.1028	0.0475	0.0952	-0.0476
	(0.0322)***	(0.0143)***	(0.0158)***	(0.0122)***
Design	-0.1697	-0.0787	-0.0738	-0.005

	(0.0376)***	(0.0167)***	(0.0185)***	(0.0143)
Economics and Accounting	-0.1275	-0.0557	-0.0462	-0.0095
	(0.0306)***	(0.0136)***	(0.0151)***	(0.0116)
Education and Training	0.0562	0.0254	-0.0025	0.0279
	(0.0340)*	(0.0151)*	(0.0167)	(0.0129)**
Engineering and Technology	-0.0047	-0.0054	0.0003	-0.0057
	(0.0417)	(0.0185)	(0.0205)	(0.0158)
English Language	-0.0619	-0.027	-0.0374	0.0105
	(0.0405)	(0.0180)	(0.0199)*	(0.0154)
Fine Arts	0.0306	0.0128	0.0111	0.0017
	(0.0222)	(0.0098)	(0.0109)	(0.0084)
Food Production	-0.0024	-0.0021	0.0109	-0.0129
	(0.0212)	(0.0094)	(0.0104)	(0.0080)
Foreign Language	0.0664	0.0318	0.0332	-0.0014
	(0.0244)***	(0.0108)***	(0.0120)***	(0.0093)
Geography	0.1351	0.0629	0.0503	0.0126
	(0.0301)***	(0.0133)***	(0.0148)***	(0.0114)
History and Archeology	-0.033	-0.0142	-0.0321	0.0179
	(0.0278)	(0.0123)	(0.0136)**	(0.0105)*
Law and Government	-0.0108	-0.0045	0.0198	-0.0243
	(0.0336)	(0.0149)	(0.0165)	(0.0128)*
Mathematics	0.0466	0.0197	0.0163	0.0034
	(0.0321)	(0.0142)	(0.0158)	(0.0122)
Mechanical	-0.2357	-0.1017	-0.127	0.0253
	(0.0453)***	(0.0201)***	(0.0223)***	(0.0172)
Medicine and Dentistry	-0.0145	-0.0066	-0.0021	-0.0045
	(0.0245)	(0.0109)	(0.0120)	(0.0093)
Personnel and Human Resources	0.0721	0.0338	0.0215	0.0123
	(0.0334)**	(0.0148)**	(0.0164)	(0.0127)
Philosophy and Theology	0.0379	0.0148	0.034	-0.0192
	(0.0326)	(0.0144)	(0.0160)**	(0.0124)
Physics	0.0764	0.0343	0.0197	0.0146
	(0.0342)**	(0.0152)**	(0.0168)	(0.0130)
Production and Processing	-0.0771	-0.0373	-0.0012	-0.0361
	(0.0255)***	(0.0113)***	(0.0125)	(0.0097)***
Psychology	-0.0934	-0.0386	-0.0495	0.0109
	(0.0363)**	(0.0161)**	(0.0178)***	(0.0138)
Public Safety and Security	-0.0802	-0.0358	-0.0169	-0.0189
	(0.0262)***	(0.0116)***	(0.0128)	(0.0099)*

Sales and Marketing	0.0003	-0.0006	-0.0008	0.0002
	(0.0296)	(0.0131)	(0.0145)	(0.0112)
Sociology and Anthropology	0.0728	0.0308	0.0272	0.0036
	(0.0359)**	(0.0159)*	(0.0176)	(0.0136)
Telecommunications	0.0567	0.0242	0.0219	0.0023
	(0.0255)**	(0.0113)**	(0.0125)*	(0.0097)
Therapy and Counseling	0.003	0.001	0.0023	-0.0013
	(0.0313)	(0.0139)	(0.0154)	(0.0119)
Transportation	-0.0868	-0.0404	-0.052	0.0116
	(0.0255)***	(0.0113)***	(0.0125)***	(0.0097)
Industry Employment Shares	0.1185	0.0493	0.0017	0.0477
	(0.0696)*	(0.0309)	(0.0342)	(0.0264)*
Industry Shares Squared	-0.4814	-0.2099	-0.1348	-0.0751
	(0.1700)***	(0.0754)***	(0.0835)	(0.0645)
Occupation Shares Across Industries	-0.1835	-0.0818	-0.0798	-0.002
	(0.0398)***	(0.0176)***	(0.0195)***	(0.0151)
Occupation Shares Squared	0.0888	0.04	0.0396	0.0003
	(0.0268)***	(0.0119)***	(0.0132)***	(0.0102)
Constant	0.2789	0.1261	0.117	0.0092
	(0.0159)***	(0.0071)***	(0.0078)***	(0.0060)
R Squared	0.05	0.05	0.04	<0.01
Sample Size	70,876	70,876	70,876	70,876

* p<0.1; ** p<0.05; *** p<0.01

Table 1: Correlation matrix of multidimensional distance measures and summary statistics.

Correlation Matrix						
Multi-Dimensional Distance Measure	Abilities	Act-ivities	Skills	Know-ledge	Shares of Industry	Shares of Occ.
Abilities	1					
Activities	0.8094	1				
Skills	0.8992	0.8481	1			
Knowledge	0.7369	0.7571	0.7561	1		
Shares of Industry Employment (Across Industries)	-0.0115	-0.0362	-0.0083	-0.0891	1	
Shares of Occupation Employment (Across Industries)	0.2624	0.2429	0.2229	0.3289	-0.0174	1

Summary Statistics						
Variable	n	Mean	Std. Dev.	Skewness	Min	Max
Abilities	70,876	0.0266	0.0096	0.2011	0	0.0569
Activities	70,876	0.0291	0.0105	0.3801	0	0.0632
Skills	70,876	0.0315	0.0136	0.4347	0	0.0768
Knowledge	70,876	0.0351	0.0104	0.0881	0	0.0702
Shares of Industry Employment (Across Industries)	70,876	0.1020	0.0962	1.7315	0	0.6539
Shares of Occupation Employment (Across Industries)	70,876	0.7211	0.2838	0.0342	0	1.4093

Table 2: Multi-dimensional distances' relations to earnings correlation.

Multi-Dimensional Distance Measure	**1**	**2**	**3**	**4**
Abilities	-1.7685	-4.5565	-3.9326	-9.7077
	(0.2504)***	(0.9288)***	(0.5645)***	(2.0942)***
Activities	-0.4703	-3.9519	-0.9751	-8.6074
	(0.1949)**	(0.7254)***	(0.4393)**	(1.6355)***
Skills	0.4760	1.5237	1.0108	2.9788
	(0.1969)**	(0.6396)**	(0.4440)**	(1.4421)**
Knowledge	-0.7425	-2.5981	-1.6381	-6.1058
	(0.1641)***	(0.6813)***	(0.3700)***	(1.5361)***
Shares of Industry Employment (Across Industries)	-0.0366	0.0286	-0.0796	0.0692
	(0.0108)***	(0.0294)	(0.0244)***	(0.0663)
Shares of Occupation Employment (Across Industries)	-0.0355	-0.1120	-0.0800	-0.2448
	(0.0038)***	(0.0175)***	(0.0086)***	(0.0395)***
Abilities Distance Squared		57.2940		119.9830
		(16.1768)***		(36.4733)***
Activities Distance Squared		55.6364		122.0760
		(10.9183)***		(24.6172)***
Skills Distance Squared		-21.0526		-41.7887
		(8.7824)**		(19.8013)**
Knowledge Distance Squared		30.0237		71.5185
		(8.9717)***		(20.2281)***
Industry Shares Squared		-0.1510		-0.3445
		(0.0734)**		(0.1656)**
Occupation Shares Squared		0.0547		0.1184
		(0.0116)***		(0.0262)***
Dependent Variable	Earnings Correlation	Earnings Correlation	(Log of) Logit Transformed Correlation	(Log of) Logit Transformed Correlation
R Squared	0.01	0.01	0.01	0.01
n	70,876	70,876	70,876	70,876

* p<0.1; ** p<0.05; *** p<0.01. These are the estimates of the earnings correlation model using multi-dimensional distances. The emphasis in this table is on the shape of the relationships between distance and earnings correlation. In each case there is significant non-monotonicity. Abilities, Activities, and Knowledge each exhibit a U-shaped relationship with the earnings correlation, as do the industry allocation distances. All the O*Net distances have been expressed as a fraction of 1000.

Table 3: Distance measures with largest coefficients, among one-dimensional measures.

Largest Negative Contributors to EE Correlation	**Largest Positive Contributors to EE Correlation**	**Largest Negative Contributors to TT Correlation**	**Largest Positive Contributors to TT Correlation**	**Largest Negative Contributors to W Correlation**	**Largest Positive Contributors to W Correlation**
Science	Judgment and Decision Making	Service Orientation	Inductive Reasoning	Service Orientation	Inductive Reasoning
Repairing	Systems Evaluation	Installation	Active Learning	Installation	Operation Monitoring
Production and Processing	Coaching and Developing Others	Reaction Time	Operation Monitoring	Reaction Time	Response Orientation
Performing for or Working Directly with the Public	Reading Comprehension	Glare Sensitivity	Dynamic Strength	Static Strength	Active Learning
Auditory Attention	Education and Training	Operating Vehicles, Mechanized Devices, or Equipment	Response Orientation	Glare Sensitivity	Dynamic Strength
		Mechanical	Stamina	Operating Vehicles, Mechanized Devices, or Equipment	Night Vision

These are the one-dimensional distance measures that have the largest coefficient estimates in the earnings correlation regression (equation 5). The list is sorted by coefficient size, but only measures with sufficiently small standard errors are included on this table. Distinctions among the four O*Net files are not made here, in terms of which file each entry comes from. This table is intended to communicate which measures have the greatest effect on earnings correlation and through which part of the decomposition they occur (residuals or trends).

Figure 1: Distribution of the correlation coefficients, pairs of occupations' (logs of) average annual real earnings, histogram.

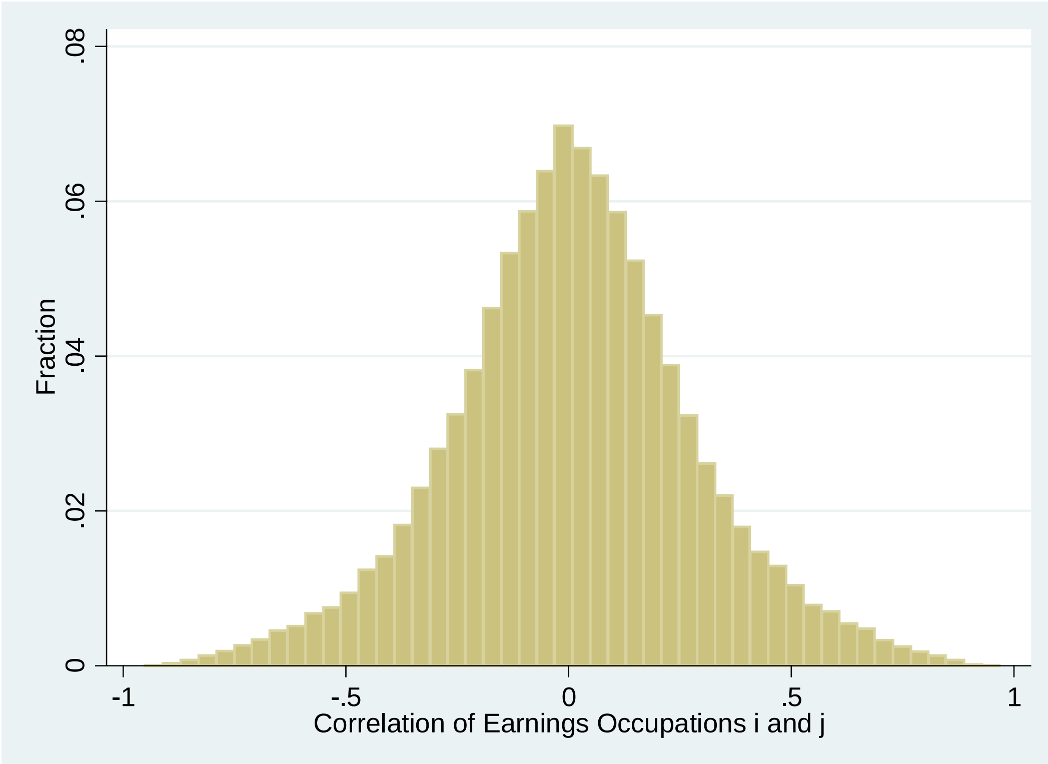
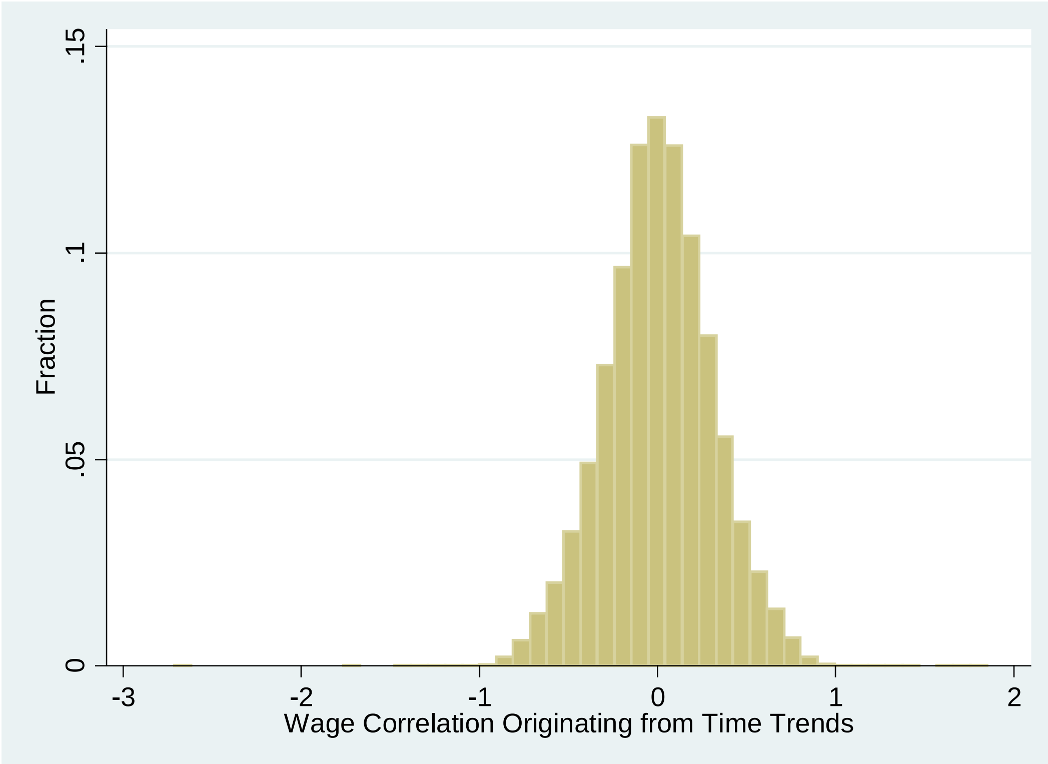
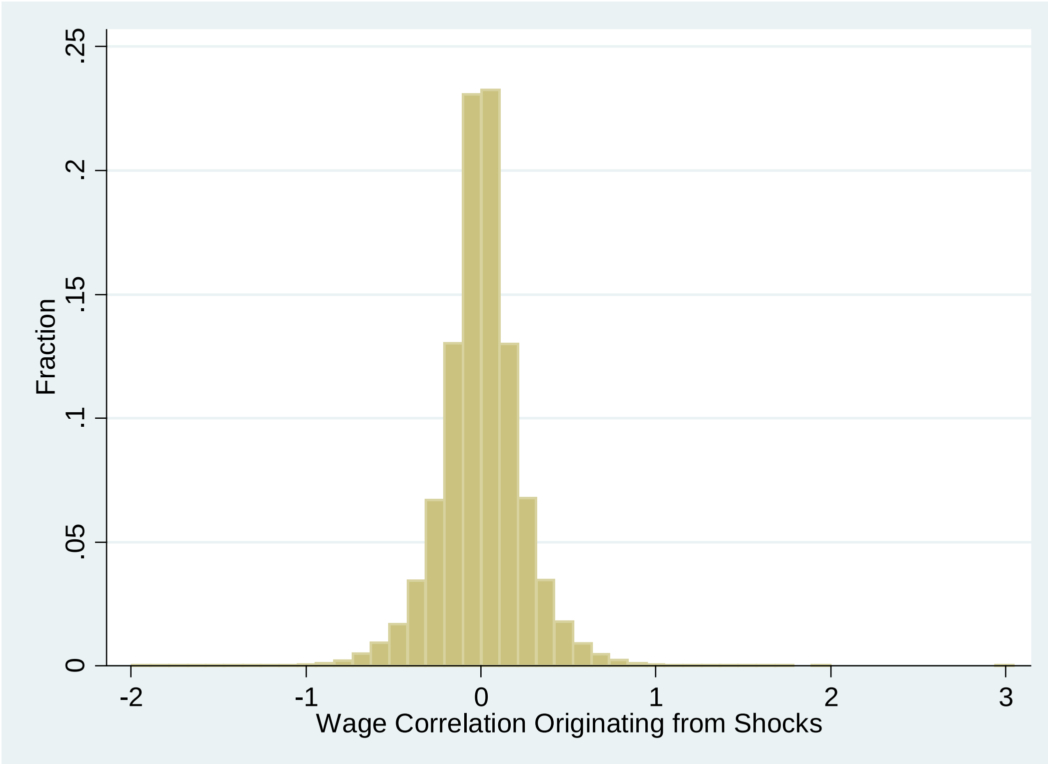


Figure 2: Distribution of the time trends' components of the correlation coefficients, pairs of occupations histogram.



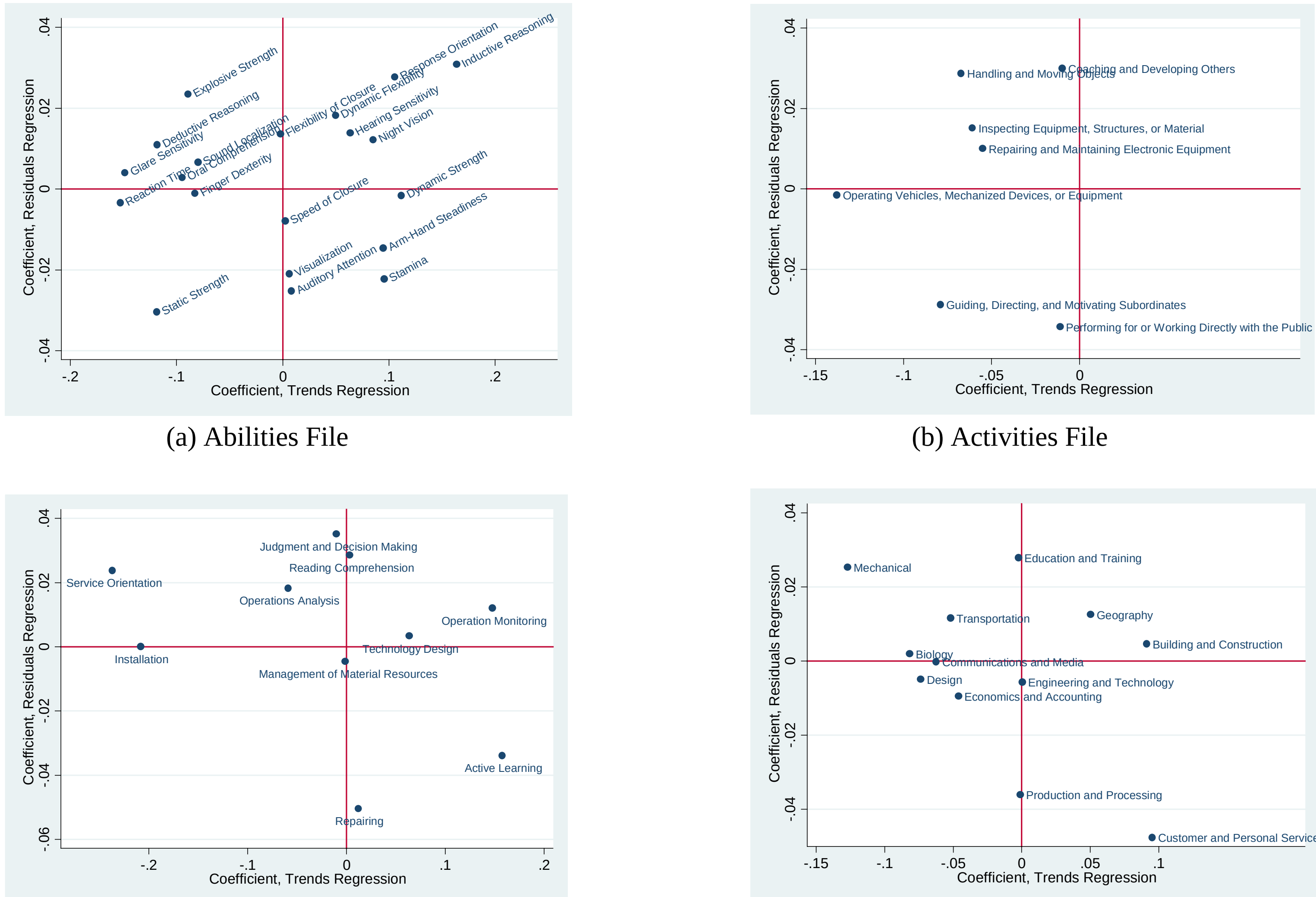
Note: The range of this histogram extends beyond the interval [-1,1] because this is only one of the two components in the decomposed correlation coefficient. This component, by itself, is not bound by the unit interval as long as the sum of this and the residuals component sums to [-1,1].

Figure 3: Distribution of the residuals' components of the correlation coefficients, pairs of occupations histogram.



Note: The range of this histogram extends beyond the interval [-1,1] because this is only one of the two components in the decomposed correlation coefficient. This component, by itself, is not bound by the unit interval as long as the sum of this and the trends component sums to [-1,1].

Figure 4: Scatterplots of regression coefficients from earnings correlation model, by O*Net file.



(a) Abilities File

(b) Activities File

(c) Skills File

(d) Knowledge File

These panels plot the coefficients from the regression of the trends component against the coefficients from the regression of the residuals component. Only variables with at least one *t* statistic > 3 in absolute value are plotted (sub-graphs by O*Net file).