On Job Requirements, Skill, and Wages

Matt Dey and Mark Loewenstein

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I. Introduction

There is a vast economic literature concerned with workers' accumulation of human capital as well as the relationship between wages and human capital, where human capital has been traditionally proxied by education. More recently, economists have begun to enrich the analysis of wages by introducing various job attributes. Most notably, attention has been placed on whether or not an individual's job is routine. Researchers have found that routine jobs pay less than jobs where workers have more independence in their decisions and actions. As computer processing power has become dramatically cheaper over time, jobs that are in the middle of the skill distribution have become more routine. Autor, Levy, and Murnane (2003), Acemoglu and Autor (2011), and other researchers have argued that this is an important factor behind the hollowing out of the wage distribution.

Papers analyzing the relationship between job attributes and wages have utilized the US Department of Labor's Dictionary of Occupational Titles (DOT) and its successor the Occupational Information Network (O*Net). However, it is fair to say that the O*Net data have not been used very thoroughly. Relatively few researchers have availed themselves of the O*Net data. Those that have used the DOT or O*NET data have generally done so in a fairly ad hoc manner, choosing one or two variables of interest and ignoring the remainder. One exception is Ingram and Neumann (2010), who merge demographic and wage information in the CPS with job characteristic information in the DOT in order to investigate the effect that job skills have on wages and how job skills have changed over time. Rather than analyzing the separate effects of the myriad job characteristics in the DOT, Ingram and

Neumann analyze returns to several latent characteristics that they obtain using factor analysis. Poletaev and Robinson (2008) and Robinson (2011) merge the wage and mobility information in the CPS and the Displaced Worker survey with job characteristic information in the DOT in order to investigate the likelihood and wage consequences of voluntary and involuntary mobility. Using factor analysis, these authors construct latent factors that they then use to measure the skill proximity of jobs.

With the exception of Poletaev and Robinson and Robinson, researchers have typically used the DOT and O*Net in a fairly ad hoc manner, choosing one or two variables of interest and ignoring the remainder. In this paper, we attempt to use the O*Net variables in a systematic fashion. Furthermore, we merge the O*Net information with the U.S. Bureau of Labor Statistics' Occupational Employments Statistics (OES) dataset. Upon doing so, we are able to analyze the relationship between a host of job attributes and wages and how the prevalence of these job attributes are changing over time.

The paper is organized as follows. Section II briefly describes the O*NET and OES data. Section III condenses the information on job attributes in O*NET using factor analysis and then analyzes the extent to which the factors can explain the variation in occupational wages at a point in time (specifically, in 2016). Section IV uses the merged O*NET-OES data to analyze how occupational employment, wages, and returns to the various factors have evolved over the period 2006-2016.

II. Description of the O*NET and OES Data

The OES survey measures occupational employment and wages in the United States by geography and industry. The OES program surveys approximately 200,000 establishments per panel (every six months), and the entire sample is surveyed over a three year period. Each year of OES data therefore contains observations from about 1.2 million establishments. Each observation contains information on both the number of employees and on the wages earned by workers in each occupation at an establishment.[1] In this draft, we use OES data from 2006 through 2016. We plan to extend the OES data to include years back to 2001 in future work.[2]

The Occupational Information Network, which is known as O*Net, provides information on job content. The data are produced under the sponsorship of the Department of Labor's Employment and Training Administration. O*Net contains occupation-level measures of the knowledge and skills required by an occupation as well as on how work is carried out. As noted above, O*Net is the successor to the Dictionary of Occupational Titles (DOT). Initially, the information in the database was collected by occupational analysts. Over time, this information has been updated by surveys of both occupation experts and each occupation's worker population.

O*Net places job attributes into a number of categories. We use many, but not all of these categories. Specifically, we choose variables in categories that represent basic job skill requirements (e.g., deductive reasoning, oral expression, trunk strength) and job attributes (e.g., frequency of decision making). However, we do not use variables in categories that describe occupation specific knowledge or interests (e.g., biology, chemistry, clerical) because these variables are not helpful in making cross-occupation comparisons. Using occupation specific job characteristics in a wage equation would be similar to simply using occupation dummies. One additional O*Net variable is of interest, the education level that is required for the job. This variable clearly differs from the year of schooling variable found in demographic data sets, but one would expect the two variables to be positively correlated: we would expect to find individuals with more schooling sorted into jobs requiring more education. Required education is coded in O*NET as a categorical variable – some high school, high school, some college, college degree, masters or Ph.D. For expositional convenience, we convert this into a continuous

[1] See Handwerker and Spletzer (2014 for a much more complete and thorough description of the OES. Handwerker and Spletzer use the OES to examine trends in wage variance.

[2] Earlier years of the data require more extensive cleaning.

variable by computing the average years of education required for the occupation. For example, if the O*NET reports that 50% of the time an occupation requires a high school degree (assigned 12 years of education) and 50% of the time an occupation requires some college courses (assigned 13 years of education), the occupation is assigned 12.5 years of education.[3] However, our results below are insensitive to whether education is treated as categorical or continuous.

The O*NET categories that we use and the variables in each category are listed in Table 1. The vast majority of the variables are self-explanatory, but explanations of all of them can be found on the O*NET website.[4] Note that the variables fall into several broad categories. The cognitive, physical, psychomotor, and sensory variables appear to measure the skills required by workers employed in an occupation. The information, interaction, mental, output, interpersonal, and structural variables would seem to describe the activities in which the workers in an occupation are engaged. Finally, the conditions variables for the most part appear for the most part to explain working conditions. We do not have a priori knowledge of which variables belong in a wage equation and therefore include all of the variables in our ensuing analysis.

III. Explaining Occupational Wage Variation with the O*NET variables

To what extent do the O*NET variables explain wage variation across occupations? To answer this question, we merge the O*NET data into the 2016 Occupational Employment Statistics data.[5] The

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[3] There are 12 education categories: Less than High School Diploma (8 years), High School Diploma (12), Post-Secondary Certificate or Some College Courses (13), Associate's Degree (14), Bachelor's Degree (16), Post-Baccalaureate Certificate (17), Master's Degree (18), Post-Master's Certificate (19), Profession Degree, Doctoral Degree, or Post-Doctoral Training (20).

[4] The Abilities variables can be found at https://www.onetonline.org/find/descriptor/browse/Abilities/, the Work Activities variables can be found at https://www.onetonline.org/find/descriptor/browse/Work_Activities/, and the Work Context variables can be found at https://www.onetonline.org/find/descriptor/browse/Work_Context/

[5] From 2006 to 2016, the OES has 792 time-consistent occupation codes. 44 of these codes are not found in the O*NET. For occupations that are not in the O*NET we find the closest (in terms of estimated occupational wage premiums from a log wage regression on geographic area, detailed industry, and occupation) occupations to the missing occupation and assign the weighted average of the O*NET variables for these occupations to the missing

first row in Table 2 shows the results of simply regressing the log of the average 2016 occupational wage against the education variable. In this equation and all that follow, we weight occupations by their total employment. Not surprisingly, an occupation's wage is strongly correlated with required education. The R squared in the regression indicates that education alone explains 66.5 percent of the variation in occupational wages.

Summary results of regressing occupational wages against the O*NET variables other than education are presented in the second row of Table 2; estimated coefficients and their standard errors can be found in Table 1. The O*NET variables as a group are exceptionally powerful in explaining occupational wage variation: the R squared in the regression is 0.933. However, the individual effects are difficult to interpret. Relatively few coefficients are significantly different from zero and a number of coefficients have signs contrary to what one would expect. This, of course, is not surprising since the O*NET variables are highly correlated with each other. As depicted in row 3, adding education to the equation adds little explanatory power, as the R squared only increases to 0.937.

There are a couple of potential reasons why the O*NET variables are highly correlated. First, many of the variables appear to measure similar attributes. Second, skills, job activities, and working conditions may not be randomly scattered across jobs, but instead may appear in patterns. Jobs invariably require a variety of skills and involve several tasks. A particular skill may have substantial value when combined with other skills and tasks, but have little value by itself. Indeed, as noted by Autor and Handel (2013), "tasks are a high-dimensional bundle of activities, the elements of which must be performed jointly to produce output. For example, flight attendants engage in both interpersonal and physical tasks, construction workers perform both analytical and physical tasks, and managers perform

occupation. This allows us to completely cover all employment in all time periods. Most of the missing occupations are residual or "All other" occupations.

both analytical and interpersonal tasks. In each case, these core job tasks cannot be unbundled; each worker occupying the job must perform them."

We begin by addressing the first reason many of the O*NET variables are correlated, namely, that they measure similar things and partially addressing the second. One potential way of dealing with this issue is simply to cherry pick variables on the basis of a priori intuition or through experimentation. We take an approach that is less ad hoc: we significantly reduce the number of variables using factor analysis.

Brief Description of Factor Analysis

In our current context, the factor analysis model can be expressed as follows. Let n be the number of occupations and p be the number of O*NET job attributes. We assume that the job attributes can be expressed as a linear function of $k < p$ underlying factors:

(1) $X - \mu = LF + e,$

where X is a $p \times n$ matrix of the variables of interest, μ is a $p \times n$ matrix of means, L is a $p \times k$ loading matrix, F is a $k \times n$ vector of common factors. The vector e is $p \times n$ vector of residuals that are independent of F as well as of each other. The errors have a diagonal covariance matrix V that is termed the uniqueness matrix and picks up variation in the observable variables that are not explained by the factors.

The following restrictions can be placed on the factors:

(2a) $E(F) = 0$

(2b) $COV(F) = I$

Let Σ be correlation matrix for the observable job attributes. One can obtain an estimate of the factor loading matrix L by finding the eigenvalues associated with the matrix $\Sigma - V$.[6] This solution is generally such that (a) most variables load on the first factors and (b) that many items load substantially on more than one factor.

Restrictions (1) and (2) do not yield a unique solution. Note that if $F' = BF$, where B is an invertible $k \times k$ matrix, then (1) is satisfied with loading factors F' and loading matrix $L' = LB^{-1}$. To aid interpretation, the initial solution is generally rotated about the origin. We choose the commonly used varimax rotation which maximizes the variance of the squared loadings in each column of L' across the variables in the rows: interpretation is made easier by the fact that factor loadings will tend to be either small or large.[7] In any case, interpreting the factors does not pose a problem in our current analysis because we carry out factor analysis within each of the O*NET categories listed in Table 1, and all of these categories have clear interpretations. Factor analysis simply provides a convenient way to weight the variables within each of the O*NET categories. It also can be thought of as reducing the measurement error associated with any of the individual variables.[8]

Having obtained a loading matrix L or L', a second step is required to obtain factor estimates, commonly referred to as factor scores. The factor scores are estimated as functions of the observable job attributes, but as there are more attributes than factors, there is an indeterminacy. One natural way of resolving this indeterminacy is through a regression-like method. Conditioning on occupation i, we may write (1) as

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[6] The above discussion leaves out some details. The uniqueness matrix V must be estimated and there is some choice with respect to the number of factors. Our criteria for the number of factors are the minimum eigenvalue is equal to 1 and the proportion of common variance accounted for by the retained factors is 0.95. The number of factors retained is the minimum number satisfying either criterion.

[7] The results we obtain are robust with respect to the rotation method that we use.

[8] In subsequent analysis, we reduce the number of variables further by performing a second stage factor analysis across O*NET categories, but we do this only to impose useful restrictions among the variables in the wage equation; our concern is still primarily with the first stage factors.

(1’) $X_i - \mu = LF_i + e_i,$

Summing over the squared residuals e_{ij} for each occupation’s j job attributes, we have

(2) $\sum_i e_{ij}^2 = (X_i - \mu - LF_i)'(X_i - \mu - LF_i)$

Choosing $\hat{F}_i$ to minimize (2) yields

(3) $\hat{F}_i = (L'L)^{-1}L'(X_i - \mu)$[9]

Factor Analysis Within the O*NET Categories

As noted above, we perform factor analysis on each of the 11 O*NET categories listed in Table 1. The factors and loading factors are shown in Table 1 and Table 3 presents the correlation matrix of the 22 variables (years of education plus 21 factors). As Table 1 indicates, we are able to reduce the twenty-one cognitive variables to two factors that we label Cognitive 1 and Cognitive 2. We reduce the nine physical job attributes to one underlying factor and the ten psychomotor variables to one factor as well. Similar data reductions occur throughout all of the categories. All in all, we are able to boil down our initial list of 148 variables to 21 factors.

As mentioned previously, jobs typically involve a bundling of skills and activities. Note that this is reflected in our results above both in the factors themselves and in the correlations among the factors. A few observations concerning some of the factors and their correlations follow. The cognitive 1 factor captures a range of cognitive skills. The correlation between this variable and education is a very high 0.86. In contrast, physical 1 picks a job’s physical requirements. Physical 1’s correlation with required education is a highly negative 0.53 and its correlation with cognitive 1 is a highly negative 0.69. In contrast, physical 1 is highly positively correlated with psychomotor 1, a factor that captures manual

[9] Naturally, L' replaces L in equation (3) when one uses the rotated loading factor matrix L'.

dexterity and related skills. Another variable of interest is Structural 1, which measures the extent to which jobs are non-routine and require independent decision making (one of this factor's major components is the variable structured versus unstructured work, which has previously received attention in the literature (for example, see Autor , Levey, and Murnane (2003) and Autor and Handel (2013)). This factor is highly correlated with both education and cognitive 1. Conditions 1 captures hazardous and unpleasant working conditions. This variable is highly correlated with physical 1, with psychomotor 1, and with jobs using machinery (output 1); it is negatively correlated with education and cognitive 1.

We have constructed cumulative distribution functions for the various factors by major occupation group. The variations in the distributions across occupations agrees quite well with one's intuition. By way of illustration, we highlight a few of these below. The remainder can be found in the appendix of our longer working paper.

As can be seen Figure 1, education is highest in professional occupations (management, business, science, and the arts) and lowest in the blue collar occupations (production, transportation and moving). Not surprisingly, the pattern for cognitive 1 and mental is similar. In contrast, physical 1 is highest in the blue collar and lowest in the professional occupations. Structural 1, which captures the importance of independent decision making, is highest in professional occupations and next highest in trades occupations (natural resources, construction, and maintenance), next highest in construction and maintenance. Trades occupations are by far the most hazardous. The next most hazardous are the blue collar jobs, and the remaining occupations are all similar in their job hazards. Output 1, which largely picks up the degree to which workers work with machines, follows a similar pattern, as does conditions 3. Interpersonal 3, which captures the extent to which a worker directs others, is highest in the professional and trade organizations. Finally, interpersonal 2, which measures the extent to which workers deal with individuals outside their employing organization, is highest in the service occupations.

It also of interest to categorize occupations on the basis of their 2006 wage and then see how the factors vary across the different wage groups.[10] Toward this end, we have placed each occupation in one of three wage groups. The first group consists of occupations whose average wage is in the bottom 20 percent. The middle group consists of occupations whose average wage is between the 20th and 80th percentile. The top group consists of occupations whose average wage is in the upper 20 percent. Figure 2 presents the relationship between wages and our variables of interest.

As expected, education is highest for the top wage group, next highest for the middle group, and lowest for the bottom group. The same is true for cognitive 1 and mental. The same pattern also holds for structural 1 and interpersonal 3. Not surprisingly, physical 1 is clearly lowest in the top wage group. But it is interesting to note that the physical 1 cdfs for the bottom and middle wage groups cross at around a probability of 0.6. While a significant portion of occupations with a high physical requirement are in the bottom wage group, a substantial portion are in the middle group. It is also the case that occupations in the middle wage group tend to be more hazardous than those in either the top or the middle wage groups. In contrast, interpersonal 2 is somewhat higher for the lowest paying occupations.

Wage Regressions

We now estimate a wage regression in which the factors and education are the explanatory variables. Recall from equation (2) that the factors have mean 0 and (approximately) have the identity matrix as their covariance matrix. In addition to estimating an equation without interactions, we also estimate an equation in which the factors are interacted. To facilitate interpretation of the latter, we transform the factors into variables are non-negative.[11] The first column in Table 4 presents the non-interacted equation. Note that the R squared in the equation is 0.861. Recall that when education and

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[10] Again, we highlight a few cdfs below. The complete set can be found in the longer online version of our paper.
[11] Specifically, letting $minF$ denote the minimum value of the factor, the transformed factor is simply $F_i^* = F_i - minF$ for all i.

all of the O*NET variables are included in the equation, the R squared is 0.937. Thus, very little information is lost when the 148 individual O*NET variables are replaced by the 21 factors. One can test this formally. Recall from equation (3) that the factor scores are simply linear combinations of the O*NET variables. One cannot reject the hypothesis that the implied restrictions on the O*NET variables in the wage equation is invalid.

Factor analysis yields a method for aggregating the individual job attributes into broader categories that can be used to explain occupational wage variation. One question that comes to mind is whether a simpler method might work just as well. An obvious alternative is to simply take an average across all of the variables in each O*NET category and then insert these averages as explanatory variables in the wage equation. When one does this, one obtains an R squared of 0.80. So while simple averages across the O*NET categories do explain most of the variation in occupational wages, the factors have significantly greater explanatory power.

Examining the estimated coefficients and standard errors, we see that education and cognitive 1 both have a positive effect on occupational wages. We also observe that less structured jobs pay more, as do jobs that involve the use of computers. It is also interesting to note that unpleasant, hazardous jobs pay more. This finding is noteworthy in light of the fact that researchers have found it notoriously difficult to find compensating wage differentials. Hazardous, unpleasant jobs tend to have other characteristics that are associated with lower wages. We suspect that we are able to tease out a positive effect for this variable because we are able to control for these other characteristics.

Note that a couple of factors in the wage equation have negative coefficients that appear puzzling at first sight. *Other things the same*, why should jobs that require more physical skills or certain sensory skills (Sensory 2) pay less? An observation is in order before answering this. As others have noted, and as the correlations in Table 3 indicate, skills and tasks tend to occur in combinations or, in other words, tend to be bundled. The coefficients in the wage equation therefore need to be interpreted with care. The coefficient for a given factor indicates the average wage return associated with that factor after taking into account the other factors the factor in question tends to be associated with. In reality, it is generally not possible for one factor to change by itself, so the factor's coefficient tells us the result of a "what if" experiment that is impossible to perform.

The implicit assumption behind the equation in column 1 is that we can isolate the wage return associated with a given factor in isolation from the other factors. In other words, the equation does not allow for possible interaction effects. A crucial feature of any job is the amount of cognitive skills that it requires. We therefore choose to interact cognitive 1 with the other factors. Column 2 shows the wage equation that results when one keeps the interactions that are significant. Throwing out interactions that are not significant makes the estimated equation easier to interpret.[12] We see that the wage return associated with a job being unstructured is greater when the job also has a greater cognitive skill requirement. The same is true of jobs that require the use of a computer, interactions with external customers, and direction of others, and certain sensory skills. The opposite is the case for jobs requiring certain other sensory skills or greater physical strength. Note that the coefficient on physical 1 by itself is positive and significant and that on sensory 2 is also positive (but not quite significant at the 5 percent level). So jobs requiring more physical skills offer a higher wage in cases where cognitive demands are low. But the return to physical skills falls as the cognitive skills required by a job increase.

The high R squared in the estimated wage equation tells us that the factors as a whole on average explain quite a bit of the variation in occupational wages. To gain further insight, we now look

[12] We obtain this equation following an iterative procedure. We first interact all variables with cognitive 1. We then discard interactions that are not significant and re-estimate the equation. We then repeat the procedure until all interaction effects are significantly different from zero.

at how successful the factors are at explaining wages at various points in the wage distribution. To fix ideas, let the wage equation be given by

(4) $w_i = \beta X_i + \varepsilon_i$,

where w_i is the average wage in occupation i and X_i is a vector of factors for occupation i with corresponding vector of coefficients β. The term ε_i is a residual error term.

Let w_g be the average value of w_i in some group g, let X_g be the average value of X_i in this group, and let ε_g be the average value of ε_i in group g. Similarly, let $\overline{w}$ be the average value of w_i across all occupations and let $\bar{X}$ be the average value of X across all occupations. Then it follows immediately from (4) that

(5) $w_g - \overline{w} = \beta\left(X_g - \bar{X}\right) + \varepsilon_g$

We define occupational group by wage decile and perform the decomposition in (5). The results appear in Table 5. We present estimates for 2006 and 2016; results are similar for the two years.) The first row in the table indicates the difference between the average wage across each decile and the mean wage across all occupations and the second row indicates the mean difference that is predicted by the mean factor values (that is, the value in the second row is simply $\beta\left(X_g - \bar{X}\right)$). The rows that follow indicate the contribution of each factor to the total predicted difference (the values in these rows therefore sum to the value in the second row). The next to last row indicates the residual unexplained difference.

For the most part, the factors do a pretty good of explaining wages throughout the entire wage distribution. The wage variation is partly explained by education, but a substantially larger fraction is explained by cognitive 1 and mental. Together cognitive 1, mental, and education explain much of the wage variation. The next most important variable is generally structural 1 (which measures nonroutineness). Conditions 1 contributes to low wages in the lowest decile and raises wage in the middle (because the lowest paying jobs are generally less hazardous than those in the middle.)

IV. Evolution of Employment and Wages Over Time

We conclude our analysis by considering how employment and wages have changed over time. The trend toward increasing inequality (as measured by an increase in the variance of wages earnings) and increasing polarization have received quite a bit of attention in the economic literature. We wish to examine what the O*NET-OES data tell us about these phenomena.

Our OES data extend from 2006 to 2016. (With a little more work, we will be able to extend the data back to 2001). Figure 3 depicts the evolution of occupational shares during the 2006-2016 period. One sees that the share of sales and office employment fell steadily and substantially throughout the entire period. The shares of trades and blue collar employment fell sharply as result of the Great Recession and then levelled off with a slight recovery. In contrast, the shares of professional and service employment rose substantially during the Great Recession and then levelled off with a slight upturn (employment in these occupations did not increase during the Great Recession, but their employment share rose because employment in the other occupations fell.) Our occupation breakdowns are a little different from those in Autor (2015), but it is still of interest to compare our results with his results for the period 2007-2012. Autor uses data from the American Community Survey.[13] Our findings look comparable to his.

Figure 4 shows how employment in the various parts of the wage distribution has evolved from 2006 to 2016. One sees that the share of employment in the group of occupations paying average wages in the 20th to 80th percentile range in 2006 fell steadily. In contrast, the share of employment in

[13] Autor analyzes earlier years using data from the Census Integrated Public Use Microdata Series files. These years are not available in the OES.

the top and bottom paying groups in 2006 increased steadily throughout the period. The OES data thus provide clear evidence of labor market polarization: employment shares rose for occupations at the ends of wage distribution and fell for those in the middle.

Since wages vary across occupations, changes in the composition of occupational employment lead directly to changes in the distribution of wages. Of course, changes in the relative payoffs to various occupations will directly lead to changes over time in the distribution of wages. Figure 5 shows how mean real wages would have evolved had occupational employment been fixed at the levels in 2006. According to the OES, real wages moved unevenly over the 2006-2016 period. Wages fell during the Great Recession, rose immediately afterwards, fell from 2010 to 2014, then increased from 2014 to 2016. Wages for the three groups largely moved in the same direction in each of these subperiods, but not always by the same amounts. Interestingly, in 2014, real wages in the bottom and middle paying occupations were at or below their 2006 levels, while real wages in the top paying group were about two percent higher. However, in the years 2014-2016, percentage wage increases in the bottom paying occupational group outpaced those in the top and middle groups, so that by 2016, wages in the bottom paying and top paying occupational groups were both about five percent above their 2006 levels, while wages in the middle paying occupational group were about two and a half percent higher than their 2006 level. Our results for the 2007-2012 subperiod are roughly similar to those in Autor (2015), who finds relatively flat wages for all groups when the endpoints for comparison are 2012 and 2007. However, as noted above, there is quite a bit of movement in wages during the years 2014- 2016.

As noted earlier, the factors are spread out unevenly across occupations. Some occupations are high in cognitive 1, some are high in physical 1, etc. Therefore changes in the composition of occupational employment imply changes in the utilization of the various factors. Furthermore, changes in the demand for the various factors might lead to changes in their returns. As shown above, variations in the factors among the various detailed occupations are able to explain most of the variations in occupational wages at a point in time. Can changes in the returns to the factors explain the observed changes in wages over time?

Changes in the factor quantities caused by differential growth rates across occupations can be decomposed into within group and between group changes. Specifically, let θ_{gt} and θ_{gs} denote the share of total employment accounted for occupations in group g in year t and year s, respectively. Then the vector of mean factor values in year t is given by

(6) $\bar{X}_t = \sum_g \theta_{gt} X_{gt}$

It follows immediately from (6) that

(7) $\bar{X}_t - \bar{X}_s = \sum_g \left[(\theta_{gt} - \theta_{gs}) X_{gs} + \theta_{gt} (X_{gt} - X_{gs}) \right].$

The first term on the right hand side of (7) is the change in mean factor quantities because of changes in employment shares across occupational groups and the second term is the change in mean factor quantities due to the changes within groups cause differential growth rates of the detailed occupations within a group.

The changes in factor quantities over the period 2006-2016 period are presented in Table 6. Most notably, there has been a shift toward jobs that require more education and more cognitive skills. This employment shift has occurred both within and across groups (which we have again defined by the 2006 wage deciles.) The magnitudes of the changes in the factors do not by themselves readily lend themselves to interpretation. The estimates in the fifth column of the table are obtained by multiplying the total changes in the factors (the first column of the table) by the factor coefficients in the wage equation. These estimates indicate the implied change in the average wage resulting from the changes in the factor quantities over time. We see that the change in education implies a 0.8 percent in the average wage level and the change in cognitive 1 implies a 1.1 percent change in the average wage level.

Table 4 shows the estimates one obtains when one estimates the wage equation for the year 2006 as well as for 2016. Differencing the coefficients between the two years yields estimates of the changes in the returns to the various factors. Alternatively, one can estimate an equation in which the dependent variable is the difference in the log wage between the two years. The results of the latter estimation using 2006 employment weights are shown in Table 7.[14] The results indicate a substantial increased return to working with computers (output 1). The return to jobs with a management component (interacting 1 and interpersonal 3) increased. The return to education also increased. Surprisingly, the return to cognitive skills and the ability to think creatively (mental) appear to have fallen. However, note that the estimates for the interacted equation indicate that the return to cognitive skills in management settings (interpersonal 3) did increase. Note too that the interacted specification does substantially better in explaining wage changes than non-interacted specification. (We plan to explore this further in a subsequent draft as well as the puzzling finding that the return to cognitive spells fell during the 2006-2016 period.)

Now consider how the changes in the factor quantities and prices relate to changes in wages over the period 2006-2016. From (4), the change in the mean wage from year s to year t is given by

(8) $$\bar{w}_t - \bar{w}_s = \beta_t \bar{X}_t - \beta_s \bar{X}_s = (\beta_t - \beta_s)\bar{X}_s + \beta_t(\bar{X}_t - \bar{X}_s)$$

Equation (8) decomposes the change in the average wage into two sources: a change in factor prices and a change in factor quantities. As shown above, mean factor quantities can change both within and between decile groups.

[14] Using 2006 weights would seem be analogous to the counterfactactuals presented earlier showing how wages would change if employment shares were fixed at the 2006 levels. Most of the coefficient estimates in the log difference equation are similar to the ones that one would obtain by differencing the 2016 and 2016 wage equation estimates, but there are substantial differences in a few cases.

The results of the mean wage growth decomposition can be found in Table 6. On average real wages increased by 5% between 2006 and 2016. Note that the amount due to changes in factor prices can be obtained by adding up the entries in the fourth column and the amount due to changes in average factor levels can be obtained by summing the entries in the fifth column. We therefore see that changes in factor levels accounted for 37 percent of the change in average wages (.0181/.0495). The remainder is accounted for changes in factor prices or the constant term in the regression.[15]

The next step in our analysis would be to look at how wages have changed at various points in the wage distribution. Specifically, we compare wage growth in each decile with mean wage growth across all occupations. Letting w_{gt} denote the average wage in group g in year t and letting X_{gt} denote mean factor quantities in group g in year t, we have

$$(9) \quad \left(w_{gt} - w_{gs}\right) - (\overline{w}_t - \overline{w}_s) = (\beta_t - \beta_s)\left(X_{gs} - \bar{X}_s\right) + \beta_t\left[\left(X_{gt} - X_{gs}\right) - (\bar{X}_t - \bar{X}_s)\right]$$

We have computed these estimates in (9), but are not yet ready to present the results. This remains for a future draft.

V. Conclusion

The analysis in this paper demonstrates the payoff to combining the O*NET and OES data sets. OES is an excellent source of annual information on occupational employment and wages in the United States. O*NET is a rich source of information on occupational characteristics. We have used factor analysis to condense the O*NET information. To aid in the interpretation of the factors, we perform separate factor analyses for the various O*NET categories.

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[15] Recall that we have normalized the factors by adding in constants to ensure that they take on non-negative values. This does not affect the coefficient estimates on the various factors, but it does affect the intercept in the wage equation as well as the individual estimates in column 4 of Table 5. We can estimate how the changes in all factor prices taken together plus the intercept affects average wage growth, but we cannot estimate the individual effects separately.

The O*NET variables taken altogether explain a high proportion of the observed variation in occupational wages. Not surprisingly, required education alone explains quite a bit of wage variation, but quite a bit more of the wage variation can be explained when one adds the O*NET variables. Furthermore, little information is lost when the individual O*NET variables are replaced by the factors. The estimated wage equation indicates that jobs requiring more education, more cognitive skills, the use of computers and more independent decision-making pay more. Other things the same, unpleasant, hazardous jobs also pay more.

OES provides evidence of a hollowing out of the wage distribution from 2006 to 2016. The share of employment at both the top and the bottom of the wage distribution increased during this period while the share of employment in the middle fell. In addition, wages at the top and the bottom of the 2006 wage distribution increased by a greater percentage than wages in the middle of the distribution.

Changes in the composition of occupational employment imply changes in the utilization of the various factors. Furthermore, changes in the demand for the various factors might lead to changes in their returns. About 37 percent of the change in average wages from 2006 to 2016 can be explained by changes in factor levels. The rest can be attributed to changes in factor prices or the wage equation intercept.

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Table 1. O*NET variable list

O*NET Category	Loading factors 1	2	3	4	Standardized scoring coefficients 1	2	3	4	2016 log wage regression results Estimate	SE	t-stat	Pr > |t|
Abilities: Cognitive Abilities												
Oral Comprehension	92	19			0.1212	-0.0606			0.0198	0.0454	0.44	0.66
Written Comprehension	94	16			0.1172	-0.0770			0.0215	0.0419	0.51	0.61
Oral Expression	92	14			0.0771	-0.0649			-0.0409	0.0398	-1.03	0.30
Written Expression	95	10			0.1941	-0.2125			0.0824	0.0359	2.30	0.02
Fluency of Ideas	87	29			0.1463	-0.0592			-0.0878	0.0473	-1.85	0.06
Originality	84	29			0.0504	0.0488			0.0670	0.0457	1.47	0.14
Problem Sensitivity	78	45			0.0391	0.0579			0.1816	0.0403	4.51	0.00
Deductive Reasoning	90	34			0.0578	0.0391			0.0522	0.0492	1.06	0.29
Inductive Reasoning	86	35			0.0928	0.0109			0.0702	0.0429	1.63	0.10
Information Ordering	78	47			0.0042	0.1370			-0.0407	0.0419	-0.97	0.33
Category Flexibility	82	35			0.0500	-0.0228			-0.1504	0.0428	-3.52	0.00
Mathematical Reasoning	83	22			0.1114	-0.0482			0.0729	0.0354	2.06	0.04
Number Facility	78	23			0.0712	-0.0360			-0.0615	0.0352	-1.74	0.08
Memorization	72	30			0.0373	0.0101			0.0143	0.0325	0.44	0.66
Speed of Closure	64	62			-0.0032	0.1610			0.0143	0.0329	0.43	0.67
Flexibility of Closure	54	69			-0.0283	0.1702			-0.0813	0.0346	-2.35	0.02
Perceptual Speed	26	83			-0.0588	0.2643			0.0694	0.0374	1.85	0.06
Spatial Orientation	-51	55			-0.0606	0.1439			-0.1017	0.0299	-3.40	0.00
Visualization	14	78			-0.0913	0.2223			-0.0216	0.0281	-0.77	0.44
Selective Attention	34	75			-0.0563	0.1719			-0.0103	0.0431	-0.24	0.81
Time Sharing	19	58			-0.0484	0.1434			-0.0718	0.0354	-2.03	0.04

Table 1. O*NET variable list (continued)

	Loading factors				Standardized scoring coefficients				2016 log wage regression results			
O*NET Category	1	2	3	4	1	2	3	4	Estimate	SE	t-stat	Pr > |t|
Abilities: Psychomotor Abilities												
Arm-Hand Steadiness	89				0.1573				-0.0062	0.0299	-0.21	0.84
Manual Dexterity	91				0.2161				0.0565	0.0297	1.90	0.06
Finger Dexterity	73				0.0164				-0.0415	0.0265	-1.56	0.12
Control Precision	93				0.0926				-0.0049	0.0252	-0.20	0.85
Multilimb Coordination	92				0.0938				0.0329	0.0238	1.38	0.17
Response Orientation	92				0.1603				-0.0645	0.0284	-2.27	0.02
Rate Control	90				0.1491				0.0260	0.0305	0.85	0.39
Reaction Time	91				0.1545				-0.0315	0.0299	-1.05	0.29
Wrist-Finger Speed	76				0.0178				0.0175	0.0188	0.93	0.35
Speed of Limb Movement	83				0.0356				-0.0115	0.0260	-0.44	0.66
Abilities: Physical Abilities												
Static Strength	97				0.1671				-0.0534	0.0277	-1.93	0.05
Explosive Strength	58				0.0282				0.0313	0.0245	1.28	0.20
Dynamic Strength	97				0.2353				0.0720	0.0329	2.19	0.03
Trunk Strength	92				0.0387				-0.0053	0.0247	-0.22	0.83
Stamina	97				0.2268				-0.0422	0.0353	-1.20	0.23
Extent Flexibility	94				0.0691				-0.0762	0.0250	-3.05	0.00
Dynamic Flexibility	64				0.0205				0.1081	0.0382	2.83	0.00
Gross Body Coordination	97				0.1839				0.0942	0.0383	2.46	0.01
Gross Body Equilibrium	91				0.0762				-0.1007	0.0311	-3.24	0.00

Table 1. O*NET variable list (continued)

O*NET Category	Loading factors 1	2	3	4	Standardized scoring coefficients 1	2	3	4	2016 log wage regression results Estimate	SE	t-stat	Pr > |t|
Abilities: Sensory Abilities												
Near Vision	8	64			0.0366	0.1116			0.1362	0.0332	4.10	0.00
Far Vision	69	34			0.1035	0.1702			0.0440	0.0271	1.62	0.11
Visual Color Discrimination	73	12			0.1851	0.1673			0.0116	0.0238	0.49	0.63
Night Vision	85	-34			0.1527	-0.0357			0.1207	0.0505	2.39	0.02
Peripheral Vision	84	-37			0.1346	-0.2624			-0.0425	0.0464	-0.92	0.36
Depth Perception	81	-27			0.1266	0.0129			-0.0012	0.0241	-0.05	0.96
Glare Sensitivity	84	-37			0.1047	-0.0764			0.0875	0.0324	2.70	0.01
Hearing Sensitivity	77	3			0.1094	0.0345			0.0351	0.0250	1.41	0.16
Auditory Attention	74	8			0.1056	0.0642			0.0735	0.0238	3.09	0.00
Sound Localization	88	-28			0.1985	0.0832			0.0312	0.0383	0.81	0.42
Speech Recognition	-20	84			0.0594	0.4061			-0.0770	0.0384	-2.01	0.05
Speech Clarity	-13	83			0.0613	0.3433			-0.0298	0.0385	-0.77	0.44
Work Activities: Information Input												
Getting Information	72				0.1759				0.0271	0.0224	1.21	0.23
Monitor Processes, Materials, or Surroundings	88				0.3227				0.0116	0.0219	0.53	0.60
Identifying Objects, Actions, and Events	86				0.2939				-0.0047	0.0199	-0.23	0.82
Inspecting Equipment, Structures, or Material	56				0.1320				-0.0138	0.0178	-0.77	0.44
Estimating the Quantifiable Characteristics of Products, Events, or Information	80				0.2133				-0.0427	0.0223	-1.91	0.06

Table 1. O*NET variable list (continued)

O*NET Category	Loading factors 1	2	3	4	Standardized scoring coefficients 1	2	3	4	2016 log wage regression results Estimate	SE	t-stat	Pr > |t|
Work Activities: Mental Processes												
Judging the Qualities of Things, Services, or People	79				0.0577				0.0154	0.0200	0.77	0.44
Processing Information	89				0.1119				-0.0291	0.0233	-1.25	0.21
Evaluating Information to Determine Compliance with Standards	82				0.0536				0.0375	0.0166	2.25	0.02
Analyzing Data or Information	94				0.1620				0.0410	0.0237	1.73	0.08
Making Decisions and Solving Problems	94				0.1761				0.0175	0.0236	0.74	0.46
Thinking Creatively	87				0.0703				-0.0057	0.0205	-0.28	0.78
Updating and Using Relevant Knowledge	91				0.0995				-0.0188	0.0231	-0.81	0.42
Developing Objectives and Strategies	91				0.1533				0.0698	0.0212	3.30	0.00
Scheduling Work and Activities	87				0.1012				-0.0185	0.0192	-0.96	0.34
Organizing, Planning, and Prioritizing Work	90				0.1069				-0.0203	0.0251	-0.81	0.42
Work Activities: Work Output												
Performing General Physical Activities	70	-56			0.1588	-0.1151			-0.0270	0.0196	-1.37	0.17
Handling and Moving Objects	67	-63			0.0225	-0.4535			0.0318	0.0180	1.77	0.08
Controlling Machines and Processes	88	-27			0.1943	0.0770			-0.0015	0.0195	-0.08	0.94
Operating Vehicles, Mechanized Devices, or Equipment	77	-27			0.0725	-0.0094			0.0204	0.0211	0.96	0.33
Interacting With Computers	-9	85			0.1467	0.3980			0.0370	0.0158	2.34	0.02
Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment	72	26			0.0999	0.1258			0.0393	0.0141	2.80	0.01
Repairing and Maintaining Mechanical Equipment	93	-20			0.4311	-0.0113			-0.0270	0.0189	-1.43	0.15
Repairing and Maintaining Electronic Equipment	84	18			0.1592	0.2656			-0.0112	0.0168	-0.67	0.50
Documenting/Recording Information	5	64			0.0554	0.1740			-0.0493	0.0187	-2.63	0.01

Table 1. O*NET variable list (continued)

O*NET Category	Loading factors 1	2	3	4	Standardized scoring coefficients 1	2	3	4	2016 log wage regression results Estimate	SE	t-stat	Pr > |t|
Work Activities: Interacting with Others												
Interpreting the Meaning of Information for Others	68	39			0.0598	0.0093			-0.0374	0.0198	-1.89	0.06
Communicating with Supervisors, Peers, or Subordinates	74	39			0.0876	0.0147			0.0420	0.0242	1.73	0.08
Communicating with Persons Outside Organization	43	79			-0.1183	0.4248			0.0211	0.0190	1.11	0.27
Establishing and Maintaining Interpersonal Relationships	50	66			-0.0170	0.1699			-0.0288	0.0217	-1.32	0.19
Assisting and Caring for Others	25	28			-0.0139	0.0762			-0.0166	0.0166	-1.00	0.32
Selling or Influencing Others	23	67			-0.1051	0.2238			0.0023	0.0150	0.15	0.88
Resolving Conflicts and Negotiating with Others	64	61			-0.0322	0.2063			-0.0496	0.0177	-2.80	0.01
Performing for or Working Directly with the Public	-6	74			-0.1330	0.2953			-0.0163	0.0128	-1.27	0.20
Coordinating the Work and Activities of Others	89	17			0.1651	-0.1482			0.0611	0.0220	2.78	0.01
Developing and Building Teams	88	25			0.1432	-0.0551			-0.0080	0.0263	-0.31	0.76
Training and Teaching Others	81	22			0.0884	-0.0479			-0.0794	0.0206	-3.85	0.00
Guiding, Directing, and Motivating Subordinates	90	22			0.2712	-0.1821			0.0437	0.0211	2.08	0.04
Coaching and Developing Others	83	31			0.1095	0.0051			-0.0157	0.0227	-0.69	0.49
Provide Consultation and Advice to Others	82	37			0.1604	-0.0402			0.0727	0.0173	4.20	0.00
Performing Administrative Activities	56	52			0.0127	0.0695			-0.0249	0.0176	-1.41	0.16
Staffing Organizational Units	82	29			0.0831	0.0056			-0.0146	0.0167	-0.87	0.38
Monitoring and Controlling Resources	79	20			0.0891	-0.0721			-0.0211	0.0159	-1.32	0.19

Table 1. O*NET variable list (continued)

O*NET Category	Loading factors 1	2	3	4	Standardized scoring coefficients 1	2	3	4	2016 log wage regression results Estimate	SE	t-stat	Pr > |t|
Work Context: Interpersonal Relationships												
Public Speaking	37	15	35		0.0317	0.0292	0.0226		0.0277	0.0207	1.34	0.18
Telephone	82	27	5		0.2380	0.1067	-0.1101		-0.0041	0.0209	-0.19	0.85
Electronic Mail	87	-11	22		0.3754	-0.2542	0.0900		-0.0034	0.0187	-0.18	0.85
Letters and Memos	80	17	18		0.1541	0.0297	-0.0358		0.0078	0.0208	0.38	0.71
Face-to-Face Discussions	48	6	46		0.0570	-0.0380	0.0984		-0.0715	0.0348	-2.06	0.04
Contact With Others	53	55	10		0.1216	0.1068	-0.0096		0.0840	0.0354	2.37	0.02
Work With Work Group or Team	34	22	62		0.0443	-0.0071	0.1531		-0.1005	0.0341	-2.95	0.00
Deal With External Customers	49	63	-6		0.0965	0.1521	-0.1113		-0.0186	0.0216	-0.86	0.39
Coordinate or Lead Others	36	17	78		0.0204	-0.0353	0.3482		0.0271	0.0293	0.92	0.36
Responsible for Others' Health and Safety	-51	25	63		-0.1905	0.0968	0.2770		0.0335	0.0231	1.45	0.15
Responsibility for Outcomes and Results	0	0	78		-0.0666	-0.1221	0.2713		0.0748	0.0245	3.05	0.00
Frequency of Conflict Situations	30	67	44		0.0154	0.2053	0.1483		-0.0296	0.0294	-1.01	0.31
Deal With Unpleasant or Angry People	5	89	5		-0.0935	0.4577	-0.1405		0.0538	0.0296	1.82	0.07
Deal With Physically Aggressive People	-11	68	21		-0.0823	0.1594	0.0099		-0.0944	0.0325	-2.90	0.00

Table 1. O*NET variable list (continued)

O*NET Category	Loading factors 1	2	3	4	Standardized scoring coefficients 1	2	3	4	2016 log wage regression results Estimate	SE	t-stat	Pr > |t|
Work Context: Physical Work Conditions												
Indoors, Environmentally Controlled	-65	-24	-14	13	-0.0337	-0.0009	-0.0203	0.0917	-0.0117	0.0158	-0.74	0.46
Indoors, Not Environmentally Controlled	84	13	1	-8	0.0959	-0.0060	-0.0868	-0.1095	-0.0072	0.0193	-0.37	0.71
Outdoors, Exposed to Weather	86	22	-29	-5	0.1758	0.1535	-0.4851	0.0199	0.0412	0.0229	1.80	0.07
Outdoors, Under Cover	84	16	-23	-2	0.0716	0.0136	-0.1301	-0.0370	-0.0697	0.0258	-2.70	0.01
In an Open Vehicle or Equipment	81	11	12	-8	0.0520	-0.0096	0.0209	-0.1091	-0.0137	0.0239	-0.57	0.57
In an Enclosed Vehicle or Equipment	75	-11	-36	-4	0.0577	0.0046	-0.1630	-0.0306	0.0358	0.0206	1.73	0.08
Physical Proximity	-15	63	-17	39	-0.0278	0.0282	-0.1006	0.1861	-0.0234	0.0217	-1.07	0.28
Sounds, Noise Levels Are Distracting or Uncomfortable	68	9	26	17	0.0035	0.0081	0.0287	0.0340	-0.0005	0.0192	-0.03	0.98
Very Hot or Cold Temperatures	81	36	7	-14	0.1058	0.0592	0.0271	-0.2545	-0.0193	0.0231	-0.83	0.41
Extremely Bright or Inadequate Lighting	85	17	12	17	0.0806	-0.0600	0.0232	0.0672	-0.0512	0.0278	-1.84	0.07
Exposed to Contaminants	68	39	30	33	0.0584	-0.0994	0.1395	0.1857	-0.0161	0.0200	-0.80	0.42
Cramped Work Space, Awkward Positions	69	31	27	39	0.0572	0.0002	-0.0311	0.2139	0.0396	0.0249	1.59	0.11
Exposed to Whole Body Vibration	81	9	19	2	0.0766	-0.0584	0.0699	-0.0098	-0.0159	0.0330	-0.48	0.63
Exposed to Radiation	1	1	8	73	-0.0150	-0.0097	-0.0273	0.1453	0.0471	0.0254	1.86	0.06
Exposed to Disease or Infections	-22	27	-16	76	-0.0332	0.0715	-0.1499	0.2536	0.0290	0.0178	1.63	0.10
Exposed to High Places	82	11	15	6	0.0900	-0.0777	0.0621	0.0316	0.0855	0.0297	2.87	0.00
Exposed to Hazardous Conditions	71	17	30	40	0.0419	-0.0800	0.0511	0.1487	-0.0299	0.0210	-1.42	0.16
Exposed to Hazardous Equipment	86	15	28	9	0.1496	-0.1249	0.1765	-0.0470	0.0421	0.0229	1.84	0.07
Exposed to Minor Burns, Cuts, Bites, or Stings	57	54	34	7	0.0103	0.0347	0.0911	-0.0310	-0.0104	0.0192	-0.54	0.59
Spend Time Sitting	-16	-94	-14	-4	0.0683	-0.3883	0.2728	0.1542	0.0148	0.0366	0.40	0.69
Spend Time Standing	14	94	19	2	-0.0791	0.3600	-0.0105	-0.1530	0.0117	0.0396	0.29	0.77
Spend Time Climbing Ladders, Scaffolds, or Poles	78	16	15	2	0.0783	0.0012	0.0153	-0.0992	-0.0338	0.0396	-0.85	0.39
Spend Time Walking and Running	19	89	13	5	-0.0388	0.1081	-0.0238	-0.0209	-0.0135	0.0260	-0.52	0.60
Spend Time Kneeling, Crouching, Stooping, or Crawling	48	64	20	20	0.0176	0.0641	0.0176	-0.0566	-0.0216	0.0299	-0.72	0.47
Spend Time Keeping or Regaining Balance	55	59	22	17	-0.0014	0.0760	-0.0120	-0.0061	-0.0044	0.0342	-0.13	0.90
Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls	38	43	66	13	-0.0169	-0.0386	0.3256	0.0012	0.0407	0.0238	1.71	0.09
Spend Time Bending or Twisting the Body	36	74	39	22	-0.0277	0.1440	0.1556	0.1046	0.0356	0.0309	1.15	0.25
Spend Time Making Repetitive Motions	-2	29	76	-6	-0.0431	-0.0025	0.2913	-0.1536	-0.0207	0.0248	-0.84	0.40

Table 1. O*NET variable list (continued)

O*NET Category	Loading factors 1	2	3	4	Standardized scoring coefficients 1	2	3	4	2016 log wage regression results Estimate	SE	t-stat	Pr > |t|
Work Context: Physical Work Conditions (continued)												
Wear Common Protective or Safety Equipment such as Safety Shoes, Glasses, Gloves, Hearing Protection, Hard Hats, or Life Jackets	56	40	36	40	0.0133	-0.0023	0.0381	0.1857	0.0070	0.0160	0.44	0.66
Wear Specialized Protective or Safety Equipment such as Breathing Apparatus, Safety Harness, Full Protection Suits, or Radiation Protection	59	18	19	58	0.0093	-0.0483	0.0099	0.2810	0.0189	0.0228	0.83	0.41
Work Context: Structural Job Characteristics												
Consequence of Error	49	31			0.0071	0.0916			-0.0107	0.0186	-0.57	0.57
Impact of Decisions on Co-workers or Company Results	88	14			0.4353	-0.0010			0.0294	0.0380	0.77	0.44
Frequency of Decision Making	78	19			0.1173	0.0597			0.0048	0.0332	0.15	0.88
Freedom to Make Decisions	85	-10			0.2532	-0.1753			0.0913	0.0310	2.94	0.00
Degree of Automation	-13	67			-0.0510	0.2215			0.0258	0.0243	1.06	0.29
Importance of Being Exact or Accurate	33	74			0.0646	0.3535			-0.0371	0.0294	-1.26	0.21
Importance of Repeating Same Tasks	0	74			-0.0773	0.3523			0.0376	0.0219	1.72	0.09
Structured versus Unstructured Work	77	3			0.2287	-0.0027			-0.0773	0.0345	-2.24	0.03
Level of Competition	45	5			0.0253	0.0110			0.0382	0.0190	2.01	0.04
Time Pressure	36	42			0.0280	0.1163			0.0384	0.0208	1.85	0.06
Pace Determined by Speed of Equipment	-34	26			-0.0378	0.1464			-0.0531	0.0238	-2.23	0.03

Table 2. Summary of 2016 log mean wage regressions

Regression	R-squared
Years of education only	0.665
148 O*NET variables	0.933
148 O*NET variables and years of education	0.937
21 factors	0.849
21 factors and years of education	0.861
21 factors, years of education, and 7 cognitive 1 interactions	0.893

Table 3. Correlation Matrix

Factor Name	Years of education	Cognitive 1	Cognitive 2	Physical	Psychomotor	Sensory 1	Sensory 2	Information Input	Interacting with Others 1	Interacting with Others 2	Mental Processes	Work Output 1	Work Output 2
Years of education		0.87	0.17	-0.53	-0.48	-0.08	0.74	0.61	0.62	0.37	0.83	-0.19	0.67
Cognitive 1	0.87		0.03	-0.69	-0.64	-0.25	0.82	0.51	0.60	0.50	0.80	-0.32	0.76
Cognitive 2	0.17	0.03		0.35	0.55	0.83	0.25	0.55	0.37	-0.18	0.33	0.66	0.17
Physical	-0.53	-0.69	0.35		0.83	0.56	-0.49	-0.08	-0.23	-0.39	-0.45	0.57	-0.71
Psychomotor	-0.48	-0.64	0.55	0.83		0.74	-0.46	0.06	-0.18	-0.47	-0.34	0.77	-0.49
Sensory 1	-0.08	-0.25	0.83	0.56	0.74		-0.04	0.38	0.15	-0.22	0.13	0.77	-0.11
Sensory 2	0.74	0.82	0.25	-0.49	-0.46	-0.04		0.49	0.52	0.52	0.67	-0.21	0.61
Information Input	0.61	0.51	0.55	-0.08	0.06	0.38	0.49		0.71	0.19	0.83	0.33	0.54
Interacting with Others 1	0.62	0.60	0.37	-0.23	-0.18	0.15	0.52	0.71		0.05	0.80	0.17	0.55
Interacting with Others 2	0.37	0.50	-0.18	-0.39	-0.47	-0.22	0.52	0.19	0.05		0.39	-0.39	0.33
Mental Processes	0.83	0.80	0.33	-0.45	-0.34	0.13	0.67	0.83	0.80	0.39		0.06	0.77
Work Output 1	-0.19	-0.32	0.66	0.57	0.77	0.77	-0.21	0.33	0.17	-0.39	0.06		-0.05
Work Output 2	0.67	0.76	0.17	-0.71	-0.49	-0.11	0.61	0.54	0.55	0.33	0.77	-0.05	
Interpersonal Relationships 1	0.66	0.81	-0.15	-0.74	-0.72	-0.34	0.67	0.24	0.28	0.65	0.59	-0.43	0.69
Interpersonal Relationships 2	-0.15	-0.06	-0.06	0.18	0.02	-0.02	0.16	-0.05	-0.14	0.46	-0.15	-0.19	-0.22
Interpersonal Relationships 3	0.36	0.27	0.37	0.13	0.10	0.24	0.32	0.45	0.65	-0.14	0.39	0.26	0.13
Physical Work Conditions 1	-0.21	-0.34	0.55	0.50	0.62	0.79	-0.28	0.14	0.05	-0.29	-0.01	0.73	-0.20
Physical Work Conditions 2	-0.55	-0.60	-0.09	0.70	0.42	0.04	-0.39	-0.38	-0.31	-0.26	-0.61	0.11	-0.76
Physical Work Conditions 3	-0.37	-0.39	0.04	0.15	0.37	0.00	-0.40	-0.13	-0.19	-0.56	-0.31	0.30	-0.15
Physical Work Conditions 4	0.28	0.15	0.36	0.22	0.28	0.25	0.28	0.51	0.20	0.04	0.25	0.25	0.07
Structural Job Characteristics 1	0.61	0.58	0.29	-0.18	-0.17	0.21	0.55	0.55	0.46	0.43	0.63	0.06	0.41
Structural Job Characteristics 2	-0.07	0.05	0.09	-0.16	0.10	-0.01	-0.07	0.14	-0.07	-0.08	0.05	0.11	0.24

Table 3. Correlation Matrix (continued)

Factor Name	Interpersonal Relationships 1	Interpersonal Relationships 2	Interpersonal Relationships 3	Physical Work Conditions 1	Physical Work Conditions 2	Physical Work Conditions 3	Physical Work Conditions 4	Structural Job Characteristics 1	Structural Job Characteristics 2
Years of education	0.66	-0.15	0.36	-0.21	-0.55	-0.37	0.28	0.61	-0.07
Cognitive 1	0.81	-0.06	0.27	-0.34	-0.60	-0.39	0.15	0.58	0.05
Cognitive 2	-0.15	-0.06	0.37	0.55	-0.09	0.04	0.36	0.29	0.09
Physical	-0.74	0.18	0.13	0.50	0.70	0.15	0.22	-0.18	-0.16
Psychomotor	-0.72	0.02	0.10	0.62	0.42	0.37	0.28	-0.17	0.10
Sensory 1	-0.34	-0.02	0.24	0.79	0.04	0.00	0.25	0.21	-0.01
Sensory 2	0.67	0.16	0.32	-0.28	-0.39	-0.40	0.28	0.55	-0.07
Information Input	0.24	-0.05	0.45	0.14	-0.38	-0.13	0.51	0.55	0.14
Interacting with Others 1	0.28	-0.14	0.65	0.05	-0.31	-0.19	0.20	0.46	-0.07
Interacting with Others 2	0.65	0.46	-0.14	-0.29	-0.26	-0.56	0.04	0.43	-0.08
Mental Processes	0.59	-0.15	0.39	-0.01	-0.61	-0.31	0.25	0.63	0.05
Work Output 1	-0.43	-0.19	0.26	0.73	0.11	0.30	0.25	0.06	0.11
Work Output 2	0.69	-0.22	0.13	-0.20	-0.76	-0.15	0.07	0.41	0.24
Interpersonal Relationships 1		0.02	0.02	-0.32	-0.66	-0.45	-0.03	0.52	0.13
Interpersonal Relationships 2	0.02		0.04	-0.14	0.33	-0.34	0.21	0.16	-0.03
Interpersonal Relationships 3	0.02	0.04		0.16	0.02	-0.10	0.37	0.44	-0.05
Physical Work Conditions 1	-0.32	-0.14	0.16		0.01	0.01	0.01	0.12	-0.01
Physical Work Conditions 2	-0.66	0.33	0.02	0.01		0.02	0.00	-0.37	-0.39
Physical Work Conditions 3	-0.45	-0.34	-0.10	0.01	0.02		0.03	-0.41	0.46
Physical Work Conditions 4	-0.03	0.21	0.37	0.01	0.00	0.03		0.34	0.13
Structural Job Characteristics 1	0.52	0.16	0.44	0.12	-0.37	-0.41	0.34		0.03
Structural Job Characteristics 2	0.13	-0.03	-0.05	-0.01	-0.39	0.46	0.13	0.03	

Table 4. 2006 and 2016 log wage regressions

	2016				2006			
	Without interactions		With Cognitive 1 interactions		Without interactions		With Cognitive 1 interactions	
Parameter	Estimate	Standard error	Estimate	Standard error	Estimate	Standard error	Estimate	Standard error
Intercept	0.8302	0.1577	1.9349	0.1853	0.9960	0.1476	1.9021	0.1760
Years of education	0.0642	0.0083	0.0418	0.0082	0.0556	0.0078	0.0395	0.0078
Cognitive1	0.2010	0.0257	-0.3027	0.0633	0.2289	0.0239	-0.2297	0.0618
Cognitive2	-0.0302	0.0183	-0.0212	0.0165	-0.0359	0.0171	-0.0340	0.0159
Physical	-0.0507	0.0222	0.0965	0.0398	-0.0667	0.0211	0.0337	0.0384
Psychomotor	0.0067	0.0253	0.0343	0.0240	0.0192	0.0238	0.0325	0.0232
Sensory1	0.1391	0.0246	0.0498	0.0322	0.1291	0.0229	0.0750	0.0306
Sensory2	-0.0705	0.0197	0.0702	0.0296	-0.0550	0.0182	0.0723	0.0285
Information	-0.0053	0.0201	-0.0210	0.0183	-0.0188	0.0188	-0.0247	0.0175
Interacting1	0.0505	0.0188	0.0269	0.0174	0.0334	0.0176	0.0184	0.0168
Interacting2	0.0372	0.0157	0.0057	0.0146	0.0208	0.0148	0.0038	0.0141
Mental	0.0496	0.0316	0.1006	0.0296	0.1042	0.0291	0.1301	0.0279
Output1	-0.0779	0.0200	-0.0680	0.0184	-0.0618	0.0188	-0.0572	0.0177
Output2	0.0554	0.0217	-0.0800	0.0376	0.0153	0.0204	-0.1063	0.0351
Interpersonal1	-0.0266	0.0208	0.0531	0.0200	-0.0267	0.0193	0.0393	0.0191
Interpersonal2	-0.0423	0.0123	-0.0738	0.0218	-0.0356	0.0114	-0.0846	0.0211
Interpersonal3	0.0575	0.0125	-0.1182	0.0223	0.0397	0.0117	-0.1072	0.0212
Conditions1	0.0867	0.0167	0.0829	0.0158	0.0979	0.0156	0.0984	0.0152
Conditions2	-0.0072	0.0187	-0.0117	0.0176	0.0003	0.0172	0.0054	0.0167
Conditions3	0.1032	0.0139	0.0902	0.0127	0.0921	0.0130	0.0878	0.0122
Conditions4	-0.0018	0.0114	0.0218	0.0108	0.0024	0.0109	0.0214	0.0106
Structural1	0.0839	0.0122	-0.0195	0.0215	0.0749	0.0110	-0.0097	0.0205
Structural2	-0.0103	0.0122	-0.0162	0.0111	-0.0072	0.0116	-0.0099	0.0107
Interactions with Cognitive1 Factor:								
Physical			-0.0732	0.0174			-0.0518	0.0171
Sensory1			0.0406	0.0123			0.0304	0.0120
Sensory2			-0.0544	0.0111			-0.0534	0.0108
Output2			0.0596	0.0144			0.0594	0.0139
Interpersonal2			0.0224	0.0085			0.0278	0.0085
Interpersonal3			0.0748	0.0099			0.0649	0.0096
Structural1			0.0451	0.0097			0.0360	0.0094
R squared	0.861		0.893		0.864		0.889	

Table 5.a. Difference between group mean and overall mean in 2006

	Decile									
Statistic	1	2	3	4	5	6	7	8	9	10
log(wage)	-0.6930	-0.5004	-0.3836	-0.2836	-0.1464	-0.0094	0.1577	0.3545	0.5508	0.9533
total explained	-0.7144	-0.4309	-0.3459	-0.2121	-0.0560	0.0348	0.1092	0.3467	0.5375	0.7311
Years of education	-0.1530	-0.0902	-0.0675	-0.0437	-0.0374	-0.0249	0.0035	0.0894	0.1404	0.1835
Cognitive1	-0.2095	-0.1934	-0.1100	-0.1123	-0.0415	-0.0763	0.0220	0.1426	0.2450	0.3336
Cognitive2	0.0260	0.0256	0.0115	-0.0021	0.0090	-0.0215	-0.0178	-0.0184	-0.0070	-0.0053
Physical1	-0.0294	-0.0347	-0.0350	-0.0047	0.0162	-0.0193	-0.0181	0.0175	0.0390	0.0685
Psychomotor1	0.0019	0.0029	0.0020	0.0067	-0.0004	0.0115	0.0059	-0.0061	-0.0073	-0.0171
Sensory1	-0.0929	-0.0617	-0.0166	0.0221	-0.0239	0.0905	0.0634	0.0464	0.0008	-0.0281
Sensory2	0.0371	0.0499	0.0227	0.0168	0.0156	0.0111	-0.0152	-0.0429	-0.0454	-0.0497
Information1	0.0203	0.0118	0.0079	0.0066	0.0031	-0.0022	-0.0038	-0.0079	-0.0169	-0.0189
Interacting1	-0.0274	-0.0157	-0.0276	-0.0179	-0.0083	-0.0044	0.0076	0.0255	0.0250	0.0431
Interacting2	-0.0004	-0.0141	0.0057	-0.0074	-0.0008	-0.0085	0.0007	0.0033	0.0137	0.0079
Mental1	-0.1435	-0.0898	-0.0578	-0.0560	-0.0085	0.0014	0.0224	0.0796	0.1091	0.1432
Output1	0.0404	0.0071	0.0100	-0.0039	-0.0009	-0.0464	-0.0252	-0.0110	0.0156	0.0142
Output2	-0.0129	-0.0135	-0.0093	-0.0034	0.0016	0.0007	0.0007	0.0073	0.0108	0.0182
Interpersonal1	0.0220	0.0249	-0.0004	0.0082	-0.0028	0.0075	-0.0031	-0.0120	-0.0219	-0.0223
Interpersonal2	-0.0227	0.0097	-0.0180	0.0036	0.0026	0.0111	-0.0001	-0.0114	0.0087	0.0166
Interpersonal3	-0.0253	-0.0023	-0.0138	-0.0107	-0.0155	-0.0133	0.0087	0.0260	0.0148	0.0314
Conditions1	-0.0732	-0.0255	0.0101	-0.0070	0.0015	0.0699	0.0395	0.0146	-0.0072	-0.0227
Conditions2	0.0004	0.0003	0.0001	0.0000	-0.0001	-0.0001	0.0000	0.0000	-0.0002	-0.0003
Conditions3	0.0167	0.0236	-0.0511	0.0380	0.0507	0.0444	0.0090	-0.0489	-0.0485	-0.0339
Conditions4	-0.0012	-0.0002	-0.0005	-0.0003	-0.0001	0.0000	0.0003	0.0005	0.0014	0.0001
Structural1	-0.0912	-0.0495	-0.0078	-0.0426	-0.0120	0.0062	0.0094	0.0508	0.0676	0.0689
Structural2	0.0035	0.0039	-0.0004	-0.0020	-0.0042	-0.0024	-0.0005	0.0017	0.0001	0.0003
residual	0.0215	-0.0695	-0.0377	-0.0715	-0.0904	-0.0442	0.0485	0.0078	0.0133	0.2221
Employment share	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000

Table 5.b. Difference between group mean and overall mean in 2016

	Decile									
Statistic	1	2	3	4	5	6	7	8	9	10
log(wage)	-0.6650	-0.5152	-0.4219	-0.2881	-0.1773	-0.0430	0.1369	0.3338	0.5309	0.9638
total explained	-0.7121	-0.4440	-0.3821	-0.2133	-0.0768	0.0188	0.1103	0.3303	0.5362	0.7357
Years of education	-0.1790	-0.1109	-0.0869	-0.0520	-0.0475	-0.0281	0.0085	0.0960	0.1626	0.2039
Cognitive1	-0.1918	-0.1766	-0.1095	-0.0986	-0.0353	-0.0716	0.0167	0.1179	0.2122	0.2814
Cognitive2	0.0213	0.0206	0.0092	-0.0032	0.0094	-0.0188	-0.0163	-0.0150	-0.0071	-0.0046
Physical1	-0.0240	-0.0267	-0.0304	-0.0040	0.0157	-0.0171	-0.0171	0.0129	0.0285	0.0505
Psychomotor1	0.0008	0.0012	0.0010	0.0024	-0.0005	0.0042	0.0027	-0.0021	-0.0024	-0.0056
Sensory1	-0.0917	-0.0622	-0.0116	0.0290	-0.0352	0.1037	0.0726	0.0518	0.0026	-0.0267
Sensory2	0.0453	0.0647	0.0332	0.0190	0.0200	0.0133	-0.0162	-0.0526	-0.0581	-0.0584
Information1	0.0057	0.0036	0.0024	0.0017	0.0011	-0.0005	-0.0012	-0.0021	-0.0049	-0.0052
Interacting1	-0.0418	-0.0261	-0.0433	-0.0280	-0.0150	-0.0070	0.0113	0.0374	0.0367	0.0646
Interacting2	-0.0037	-0.0269	0.0089	-0.0105	0.0007	-0.0148	0.0003	0.0070	0.0226	0.0115
Mental1	-0.0693	-0.0456	-0.0298	-0.0259	-0.0049	-0.0002	0.0116	0.0371	0.0518	0.0667
Output1	0.0475	0.0096	0.0101	-0.0063	0.0025	-0.0611	-0.0405	-0.0148	0.0189	0.0156
Output2	-0.0492	-0.0511	-0.0371	-0.0124	0.0061	0.0004	0.0051	0.0255	0.0387	0.0648
Interpersonal1	0.0237	0.0249	0.0009	0.0073	-0.0049	0.0078	-0.0022	-0.0116	-0.0211	-0.0215
Interpersonal2	-0.0280	0.0102	-0.0205	0.0020	0.0021	0.0131	-0.0026	-0.0136	0.0128	0.0223
Interpersonal3	-0.0334	-0.0055	-0.0206	-0.0149	-0.0243	-0.0200	0.0140	0.0352	0.0191	0.0445
Conditions1	-0.0593	-0.0200	0.0148	-0.0057	-0.0029	0.0666	0.0384	0.0147	-0.0087	-0.0185
Conditions2	-0.0094	-0.0068	-0.0035	-0.0001	0.0034	0.0021	0.0003	0.0011	0.0052	0.0073
Conditions3	0.0182	0.0313	-0.0583	0.0372	0.0547	0.0448	0.0056	-0.0499	-0.0436	-0.0302
Conditions4	0.0008	0.0002	0.0004	0.0002	0.0001	0.0000	-0.0003	-0.0003	-0.0011	0.0000
Structural1	-0.0993	-0.0576	-0.0111	-0.0474	-0.0158	0.0045	0.0203	0.0533	0.0719	0.0734
Structural2	0.0046	0.0055	-0.0005	-0.0032	-0.0062	-0.0025	-0.0005	0.0022	-0.0005	0.0001
residual	0.0472	-0.0712	-0.0398	-0.0747	-0.1006	-0.0618	0.0266	0.0034	-0.0052	0.2280
Employment share	0.1111	0.1001	0.0951	0.0905	0.0991	0.0927	0.0907	0.0954	0.1114	0.1140

Table 6. Decomposition of growth in factor means and mean log wages

Variable	Decomposition of factor means			Decomposition of growth in mean log wage over time	
	Total change	Within group change	Between group change	Change due to change in prices	Change due to change in levels
Total				0.0495	
Intercept				-0.1658	
Years of education	0.1284	0.0762	0.0522	0.1131	0.0082
Cognitive1	0.0545	0.0270	0.0275	-0.0577	0.0110
Cognitive2	-0.0078	0.0064	-0.0142	0.0234	0.0002
Physical1	-0.0211	0.0018	-0.0228	0.0223	0.0011
Psychomotor1	-0.0376	-0.0121	-0.0256	-0.0213	-0.0003
Sensory1	-0.0315	-0.0082	-0.0232	0.0212	-0.0044
Sensory2	0.0392	0.0246	0.0146	-0.0386	-0.0028
Information1	0.0352	0.0220	0.0132	0.0472	-0.0002
Interacting1	0.0433	0.0211	0.0221	0.0472	0.0022
Interacting2	0.0315	0.0180	0.0135	0.0441	0.0012
Mental1	0.0383	0.0208	0.0174	-0.1267	0.0019
Output1	-0.0356	-0.0117	-0.0239	-0.0281	0.0028
Output2	0.0261	0.0096	0.0166	0.0994	0.0014
Interpersonal1	0.0317	0.0194	0.0123	0.0003	-0.0008
Interpersonal2	0.0209	0.0260	-0.0052	-0.0187	-0.0009
Interpersonal3	0.0286	0.0184	0.0102	0.0621	0.0016
Conditions1	-0.0495	-0.0270	-0.0224	-0.0155	-0.0043
Conditions2	-0.0011	0.0056	-0.0067	-0.0190	0.0000
Conditions3	-0.0403	-0.0309	-0.0095	0.0323	-0.0042
Conditions4	0.0333	0.0318	0.0015	-0.0084	-0.0001
Structural1	0.0484	0.0391	0.0094	0.0289	0.0041
Structural2	-0.0260	-0.0164	-0.0096	-0.0105	0.0003
Total				0.0314	0.0181

Table 7. Difference in 2016 and 2006 log wage regressions (using 2006 employment weights)

	Without interactions		With Cognitive 1 interactions	
Parameter	Estimate	Standard error	Estimate	Standard error
Intercept	-0.0049	0.0434	0.0252	0.0542
Years of education	0.0052	0.0023	0.0005	0.0024
Cognitive1	-0.0289	0.0070	-0.0357	0.0190
Cognitive2	0.0032	0.0050	0.0078	0.0049
Physical	0.0151	0.0062	0.0663	0.0118
Psychomotor	-0.0164	0.0070	-0.0042	0.0071
Sensory1	0.0063	0.0067	-0.0208	0.0094
Sensory2	0.0088	0.0054	-0.0013	0.0088
Information	0.0120	0.0055	0.0090	0.0054
Interacting1	0.0173	0.0052	0.0121	0.0052
Interacting2	0.0188	0.0043	0.0115	0.0043
Mental	-0.0454	0.0086	-0.0405	0.0086
Output1	-0.0144	0.0055	-0.0101	0.0054
Output2	0.0197	0.0060	0.0252	0.0108
Interpersonal1	-0.0065	0.0057	0.0079	0.0059
Interpersonal2	-0.0133	0.0034	0.0061	0.0065
Interpersonal3	0.0122	0.0034	-0.0064	0.0065
Conditions1	-0.0052	0.0046	-0.0094	0.0047
Conditions2	-0.0152	0.0050	-0.0215	0.0051
Conditions3	0.0024	0.0038	0.0008	0.0038
Conditions4	0.0022	0.0032	0.0050	0.0033
Structural1	-0.0077	0.0032	-0.0077	0.0063
Structural2	0.0006	0.0034	-0.0020	0.0033
Interactions with Cognitive1 Factor:				
Physical			-0.0242	0.0053
Sensory1			0.0091	0.0037
Sensory2			0.0059	0.0033
Output2			-0.0037	0.0043
Interpersonal2			-0.0053	0.0026
Interpersonal3			0.0093	0.0030
Structural1			-0.0006	0.0029
R squared	0.161		0.248	

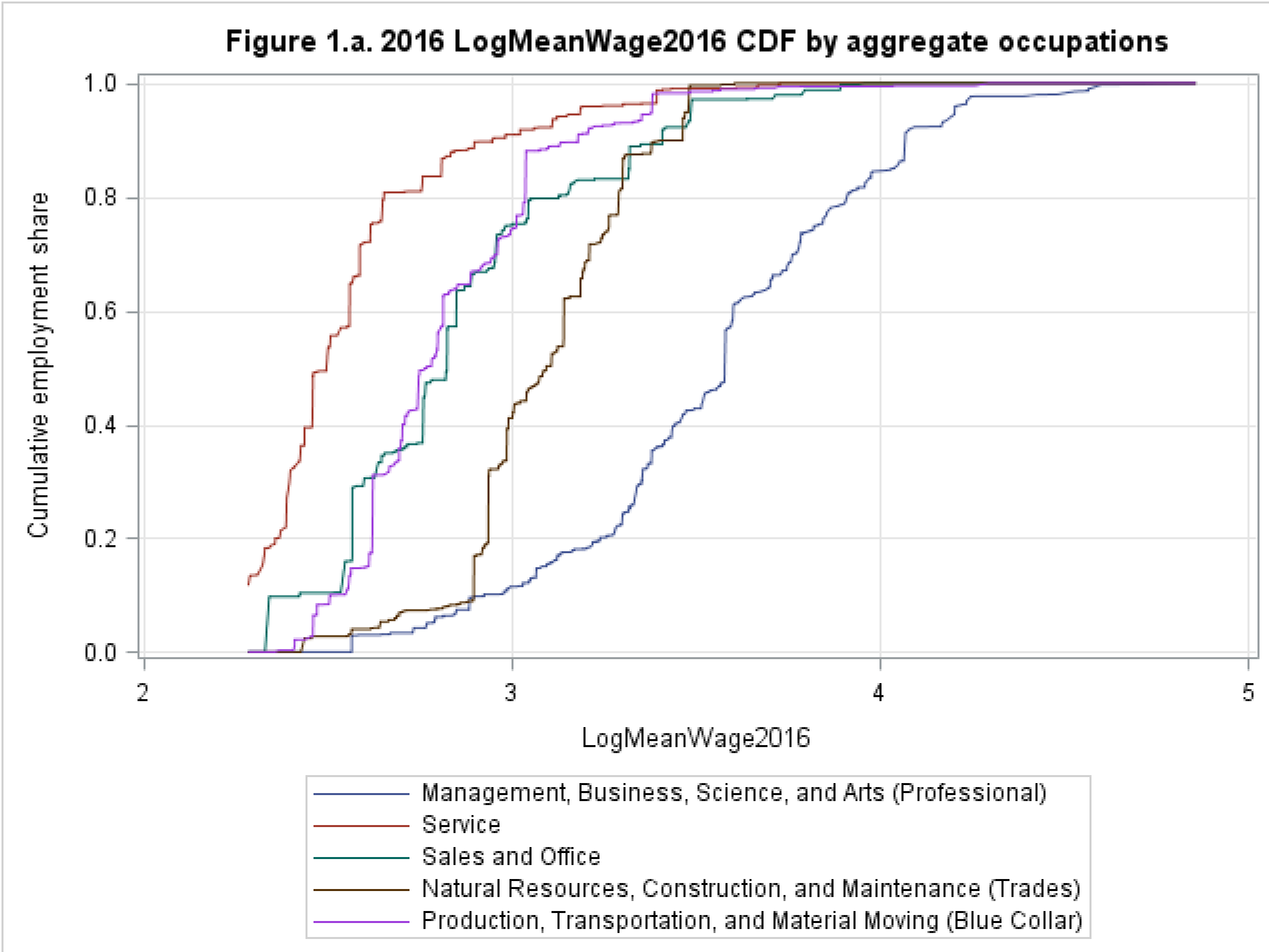


Figure 1.a. 2016 LogMeanWage2016 CDF by aggregate occupations
Cumulative employment share
0.0
0.2
0.4
0.6
0.8
1.0
2
3
4
5
LogMeanWage2016
Management, Business, Science, and Arts (Professional)
Service
Sales and Office
Natural Resources, Construction, and Maintenance (Trades)
Production, Transportation, and Material Moving (Blue Collar)

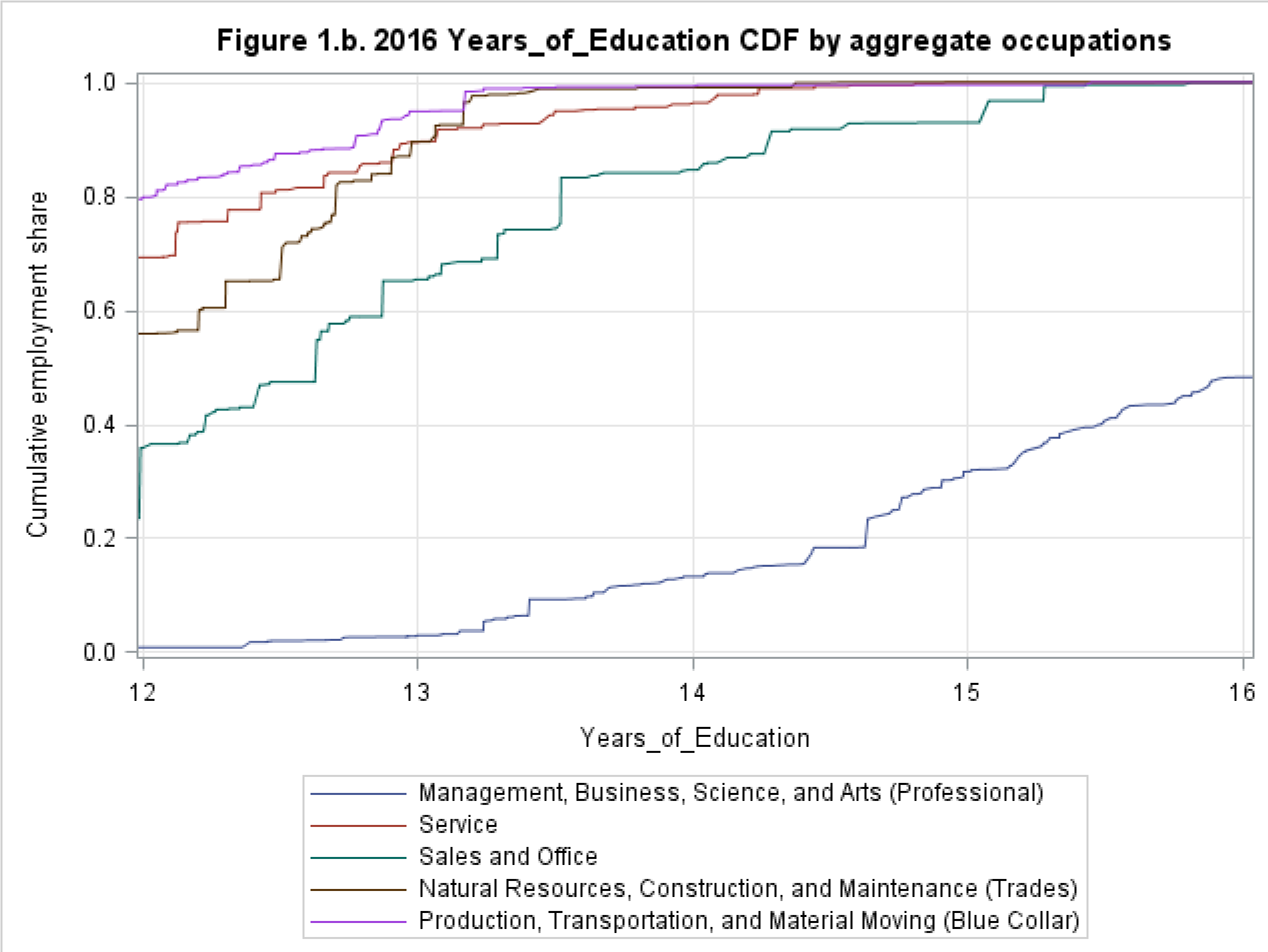


Figure 1.b. 2016 Years_of_Education CDF by aggregate occupations
Cumulative employment share
0.0
0.2
0.4
0.6
0.8
1.0
12
13
14
15
16
Years_of_Education
Management, Business, Science, and Arts (Professional)
Service
Sales and Office
Natural Resources, Construction, and Maintenance (Trades)
Production, Transportation, and Material Moving (Blue Collar)

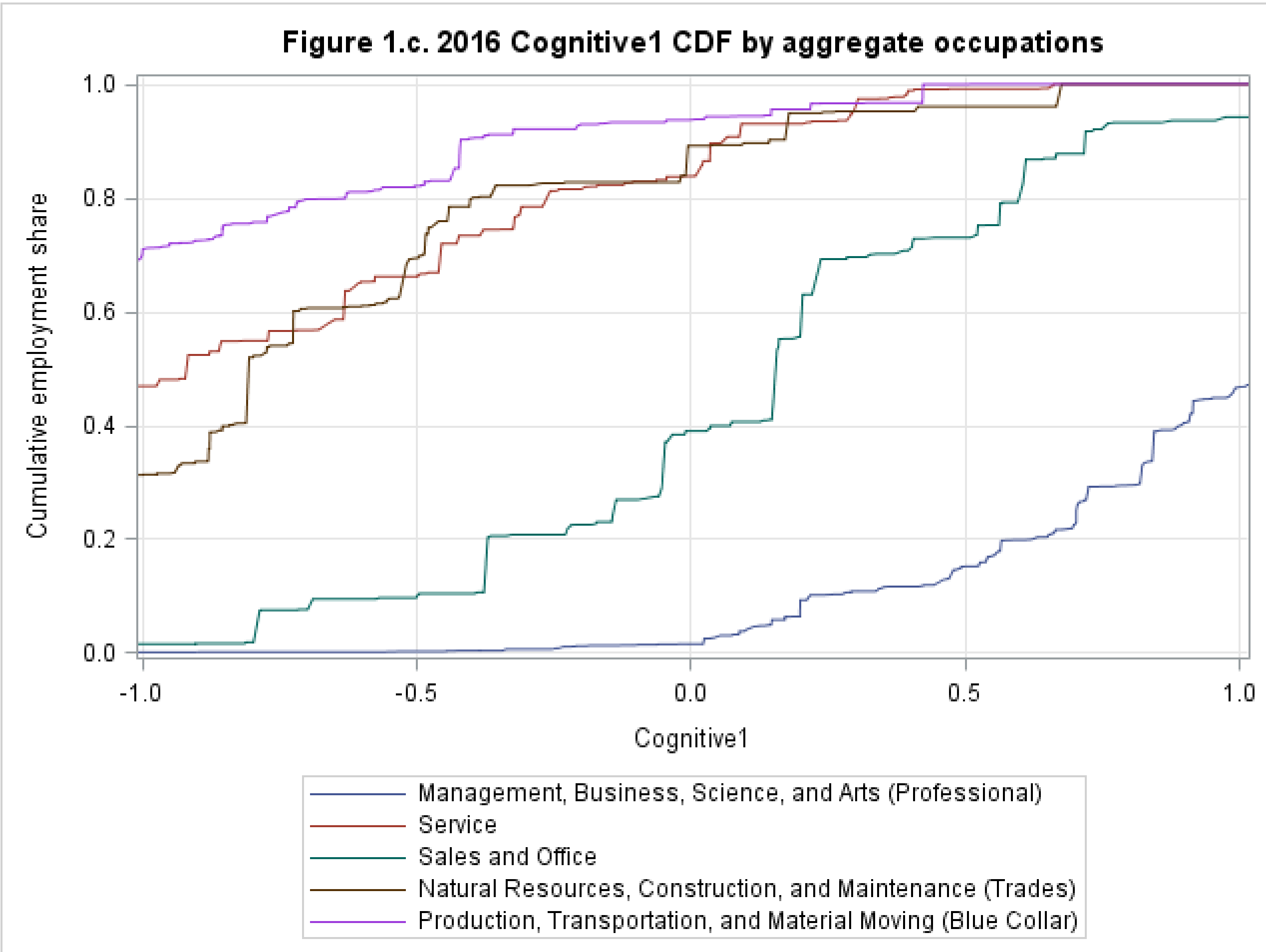


Figure 1.c. 2016 Cognitive1 CDF by aggregate occupations
Cumulative employment share
1.0
0.8
0.6
0.4
0.2
0.0
-1.0
-0.5
0.0
0.5
1.0
Cognitive1
Management, Business, Science, and Arts (Professional)
Service
Sales and Office
Natural Resources, Construction, and Maintenance (Trades)
Production, Transportation, and Material Moving (Blue Collar)

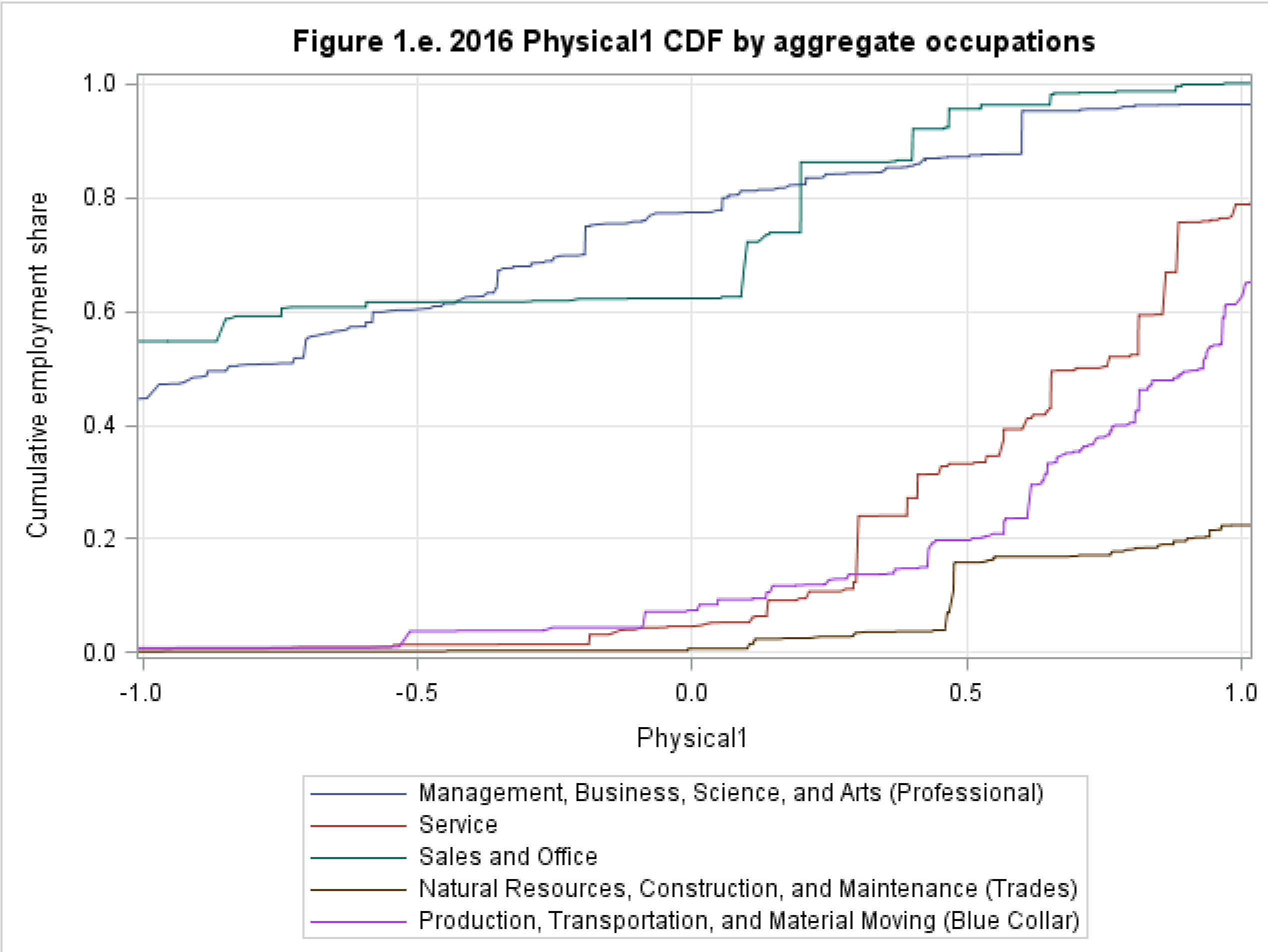


Figure 1.e. 2016 Physical1 CDF by aggregate occupations
Cumulative employment share
1.0
0.8
0.6
0.4
0.2
0.0
-1.0
-0.5
0.0
0.5
1.0
Physical1
Management, Business, Science, and Arts (Professional)
Service
Sales and Office
Natural Resources, Construction, and Maintenance (Trades)
Production, Transportation, and Material Moving (Blue Collar)

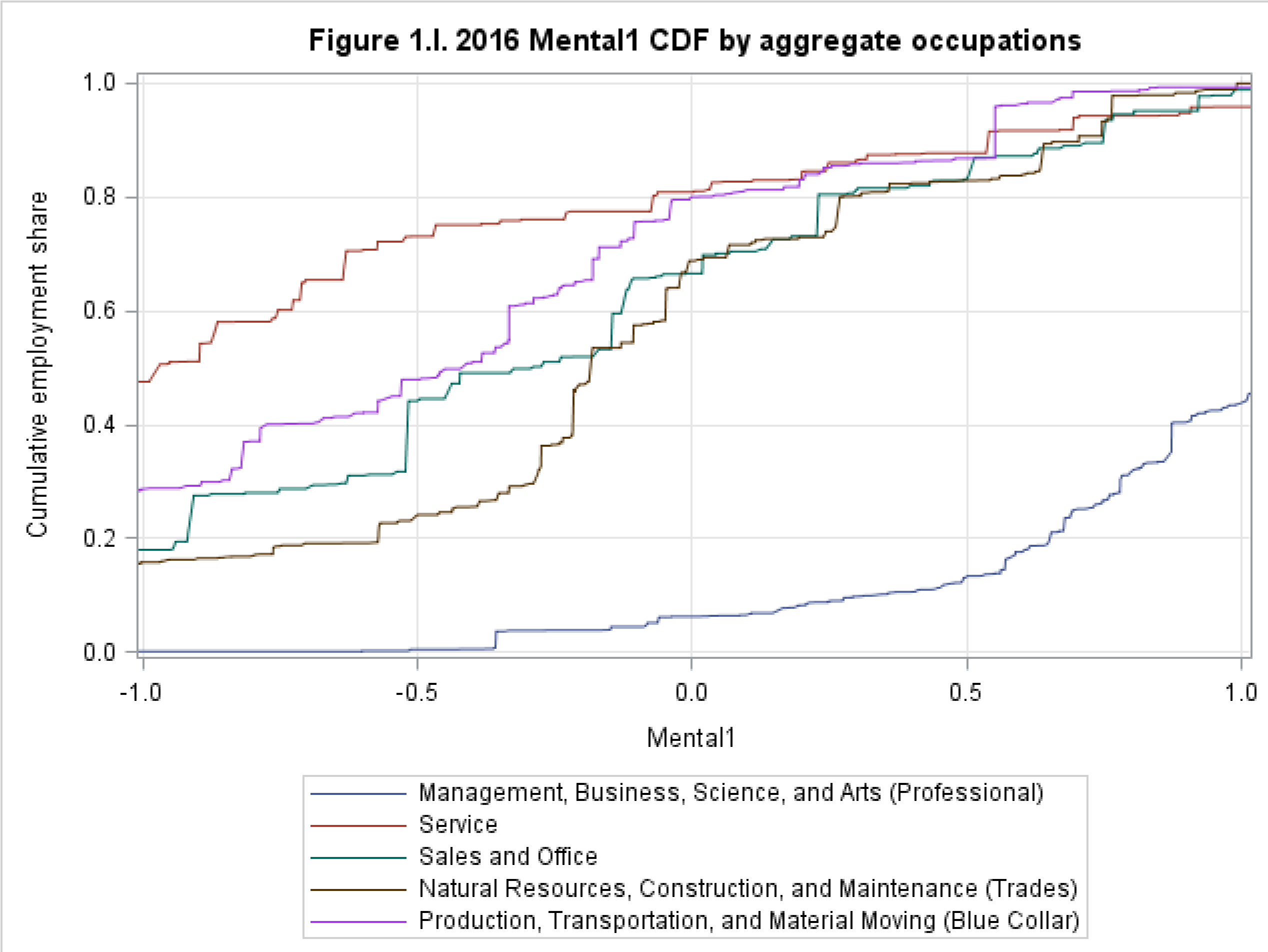
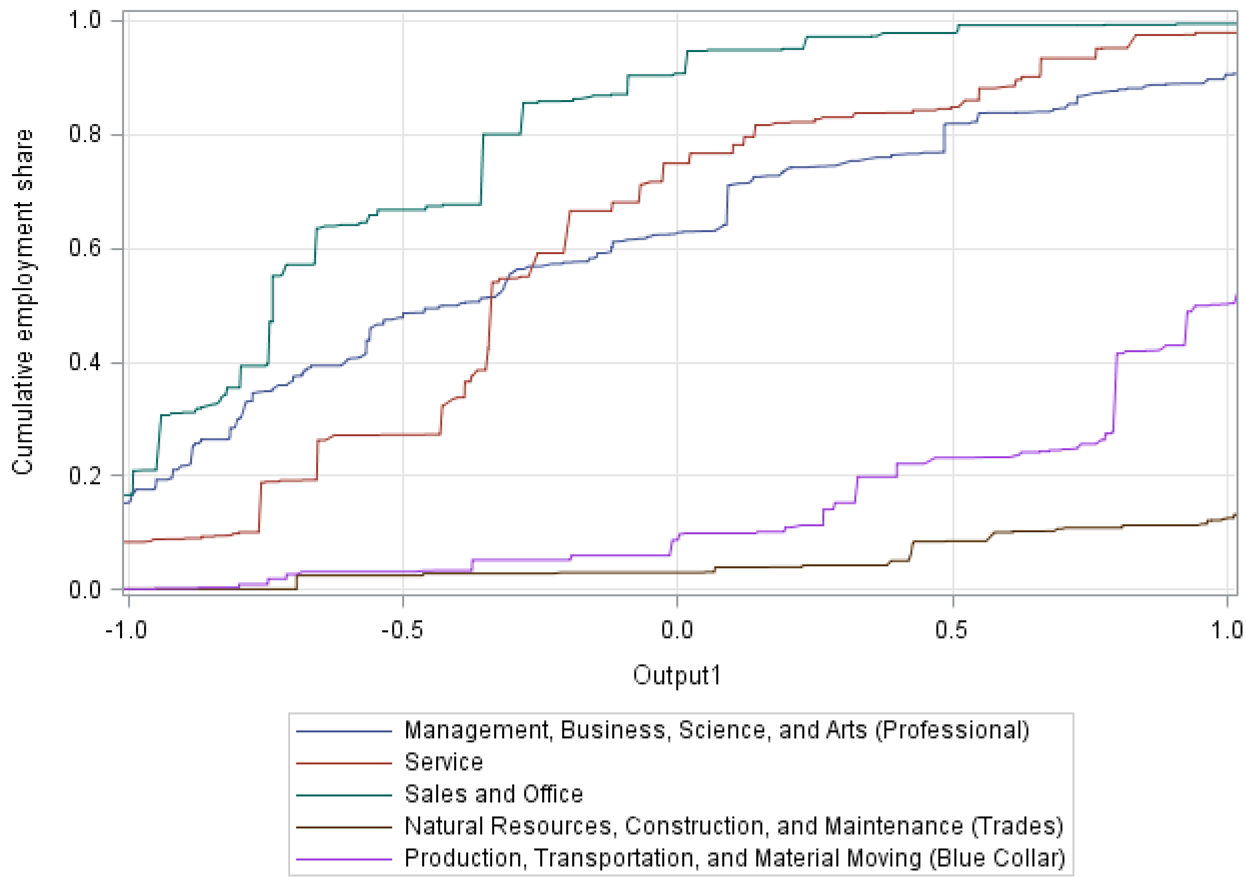


Figure 1.I. 2016 Mental1 CDF by aggregate occupations
Cumulative employment share
0.0
0.2
0.4
0.6
0.8
1.0
-1.0
-0.5
0.0
0.5
1.0
Mental1
Management, Business, Science, and Arts (Professional)
Service
Sales and Office
Natural Resources, Construction, and Maintenance (Trades)
Production, Transportation, and Material Moving (Blue Collar)

Figure 1.m. 2016 Output1 CDF by aggregate occupations



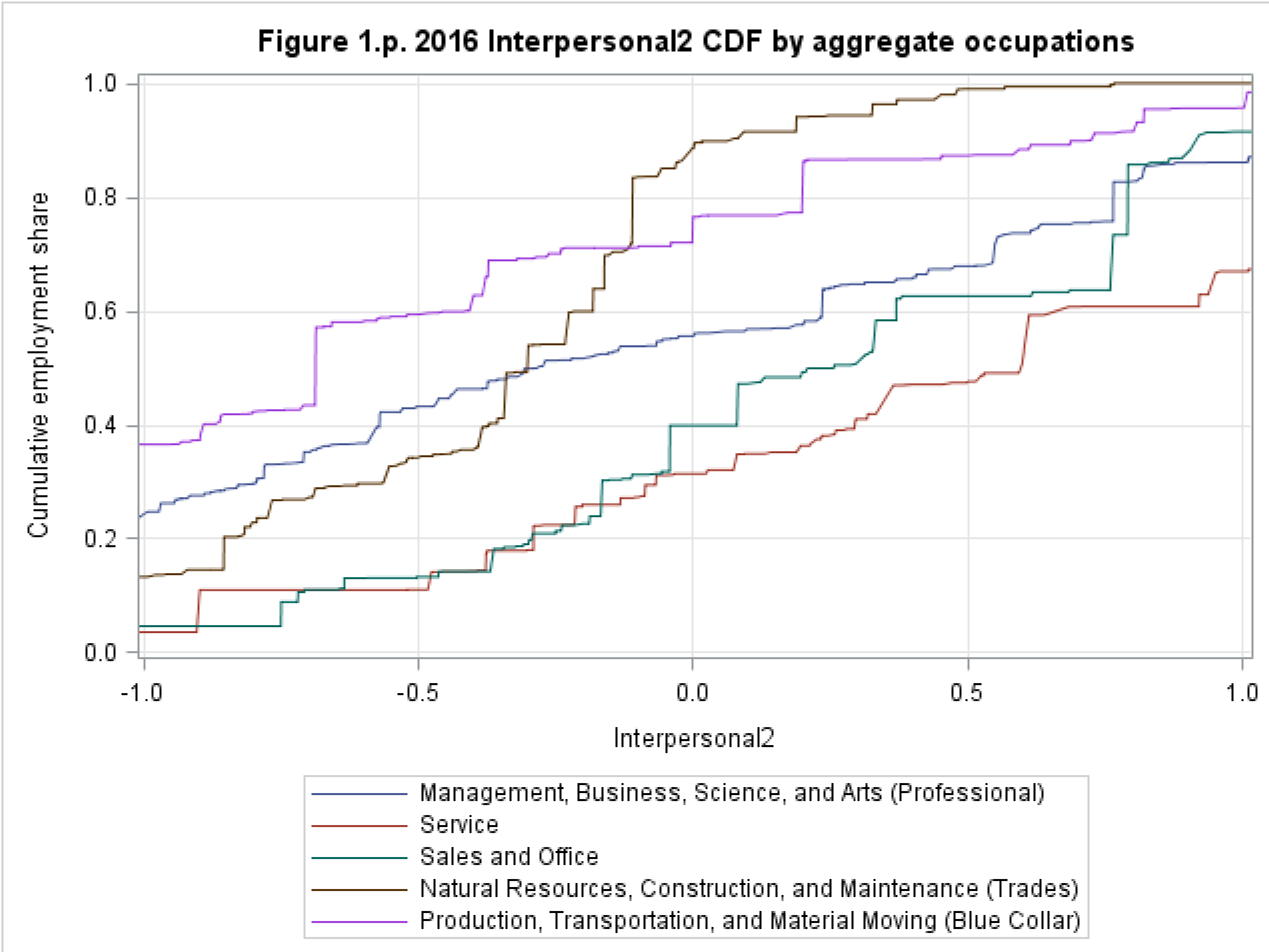


Figure 1.p. 2016 Interpersonal2 CDF by aggregate occupations
Cumulative employment share
0.0
0.2
0.4
0.6
0.8
1.0
-1.0
-0.5
0.0
0.5
1.0
Interpersonal2
Management, Business, Science, and Arts (Professional)
Service
Sales and Office
Natural Resources, Construction, and Maintenance (Trades)
Production, Transportation, and Material Moving (Blue Collar)

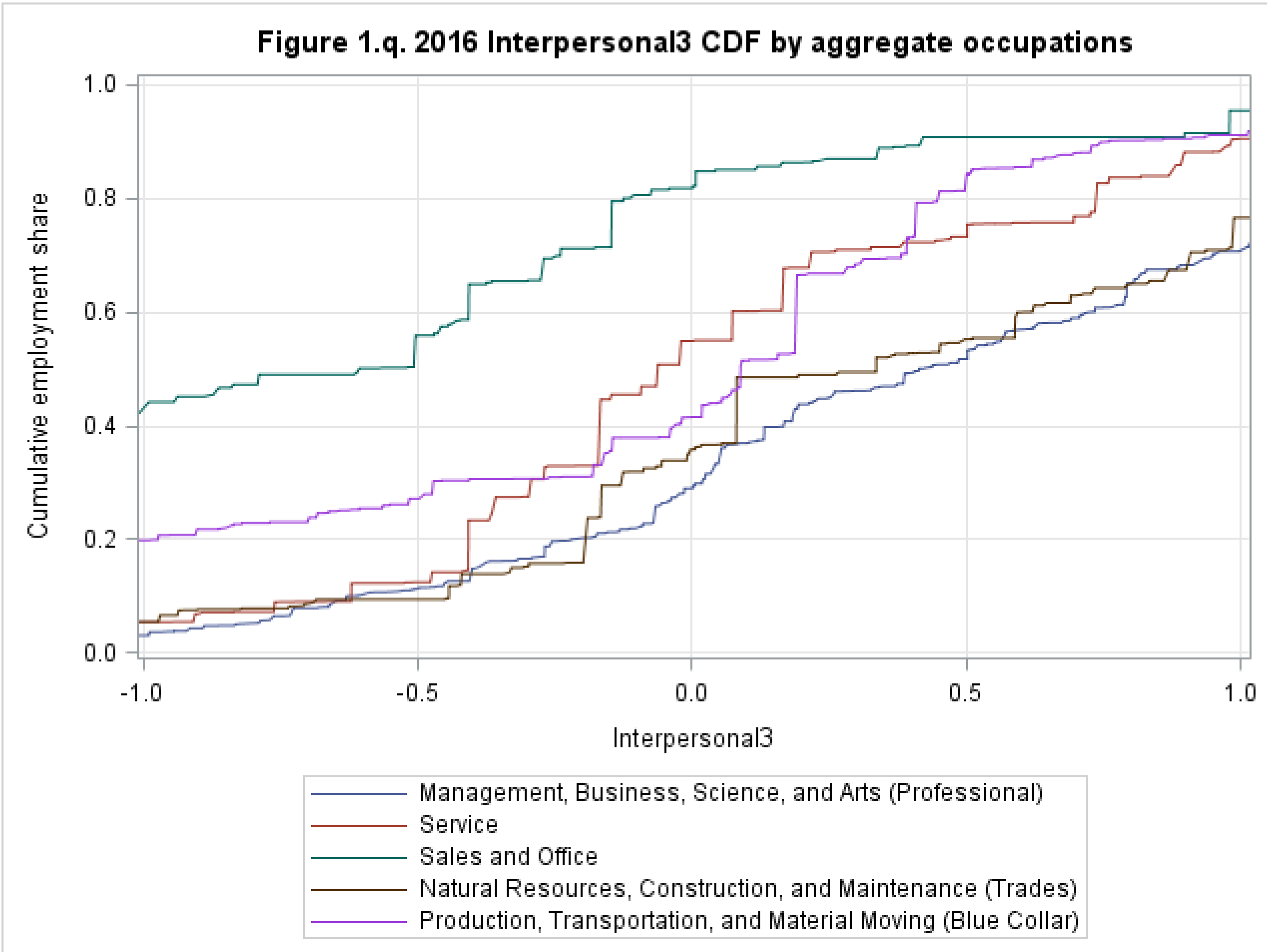
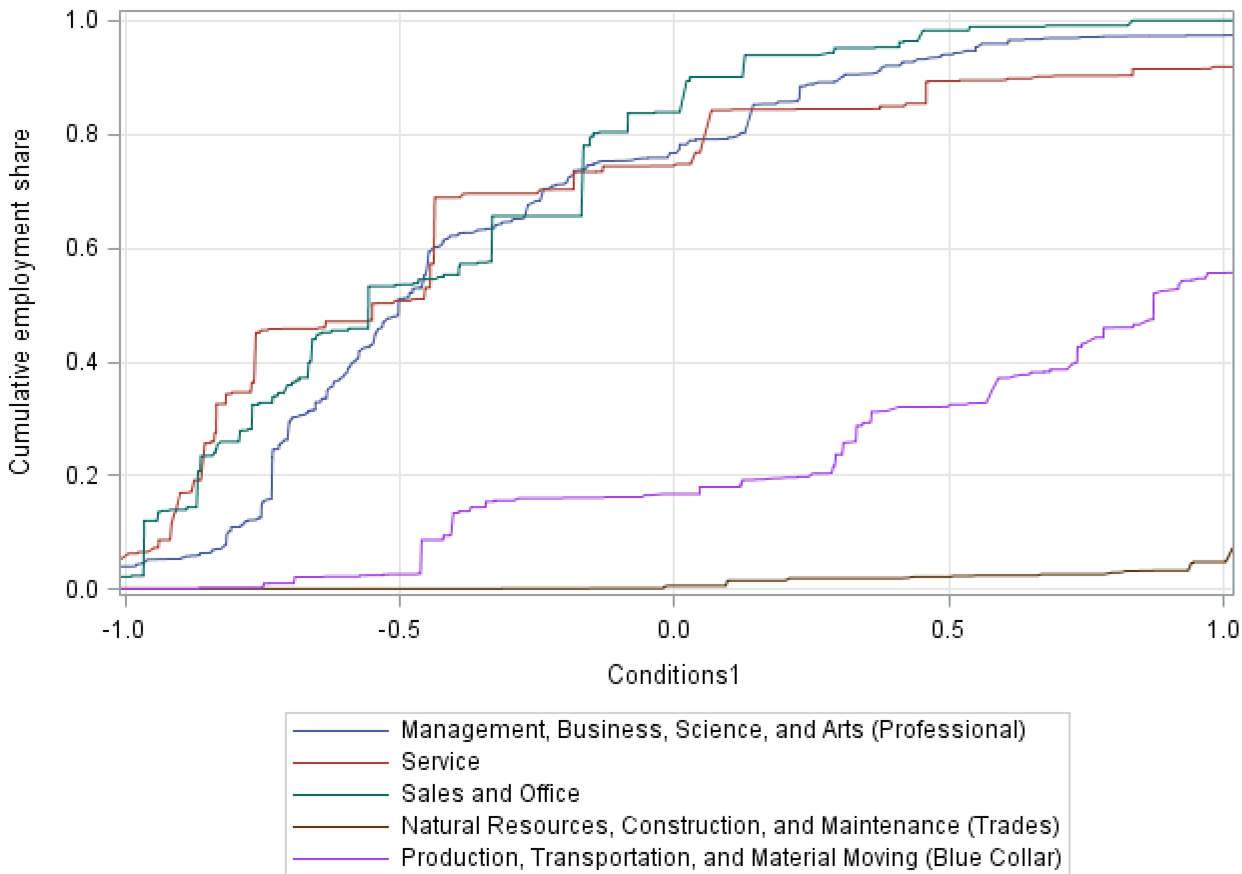


Figure 1.q. 2016 Interpersonal3 CDF by aggregate occupations
Cumulative employment share
0.0
0.2
0.4
0.6
0.8
1.0
-1.0
-0.5
0.0
0.5
1.0
Interpersonal3
Management, Business, Science, and Arts (Professional)
Service
Sales and Office
Natural Resources, Construction, and Maintenance (Trades)
Production, Transportation, and Material Moving (Blue Collar)

Figure 1.r. 2016 Conditions1 CDF by aggregate occupations



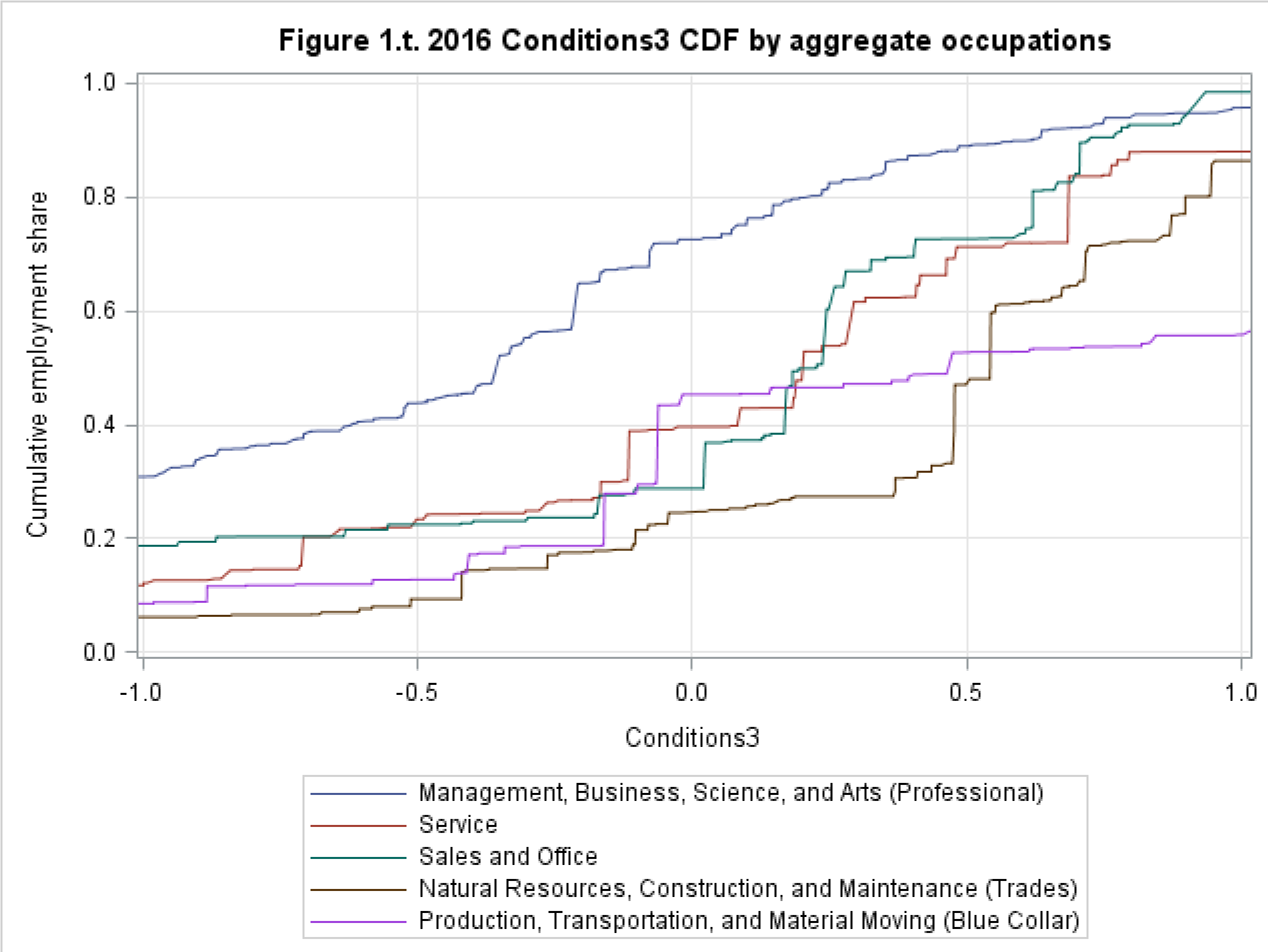


Figure 1.t. 2016 Conditions3 CDF by aggregate occupations
Cumulative employment share
0.0
0.2
0.4
0.6
0.8
1.0
-1.0
-0.5
0.0
0.5
1.0
Conditions3
Management, Business, Science, and Arts (Professional)
Service
Sales and Office
Natural Resources, Construction, and Maintenance (Trades)
Production, Transportation, and Material Moving (Blue Collar)

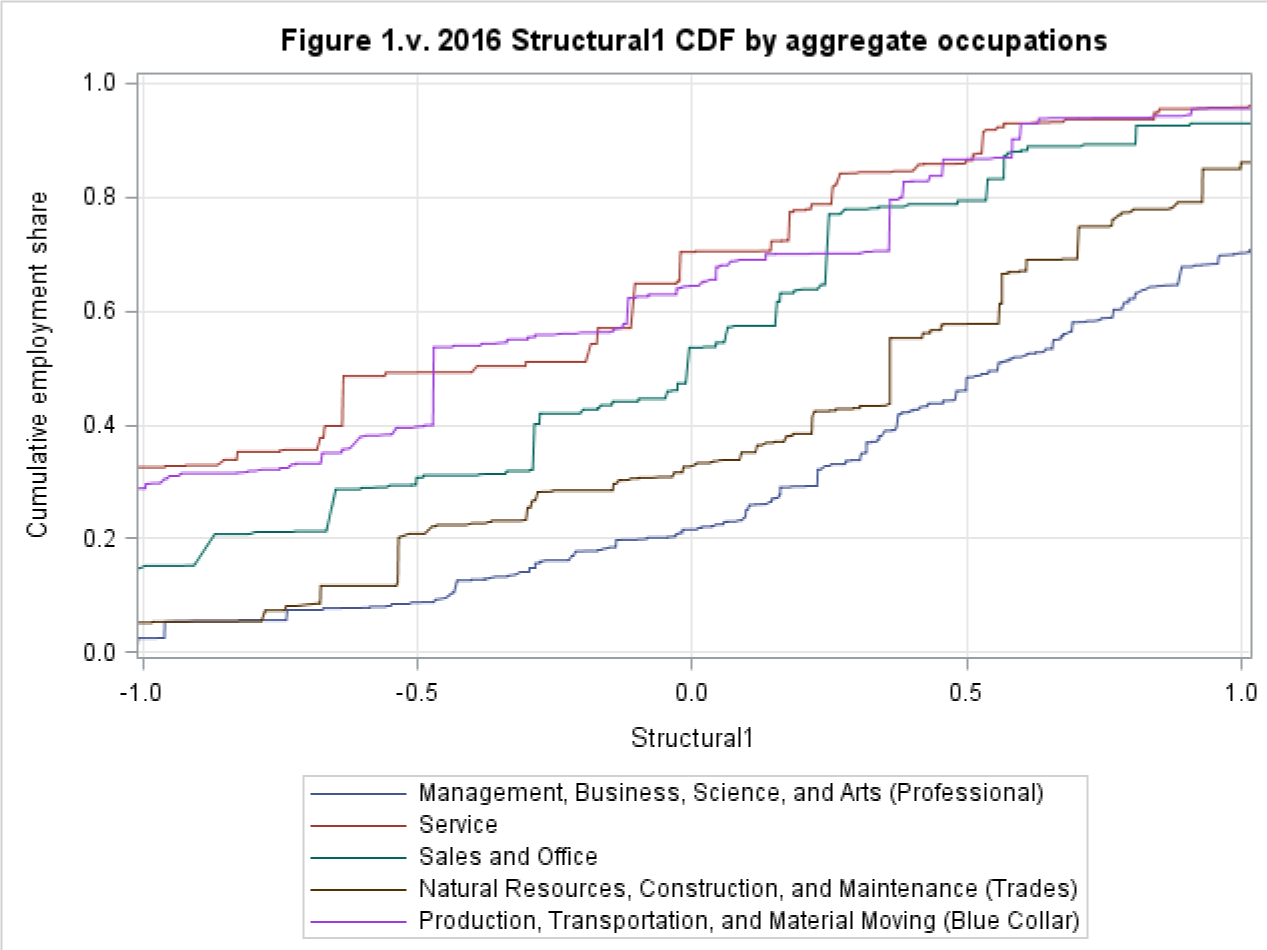


Figure 1.v. 2016 Structural1 CDF by aggregate occupations
Cumulative employment share
1.0
0.8
0.6
0.4
0.2
0.0
-1.0
-0.5
0.0
0.5
1.0
Structural1
Management, Business, Science, and Arts (Professional)
Service
Sales and Office
Natural Resources, Construction, and Maintenance (Trades)
Production, Transportation, and Material Moving (Blue Collar)

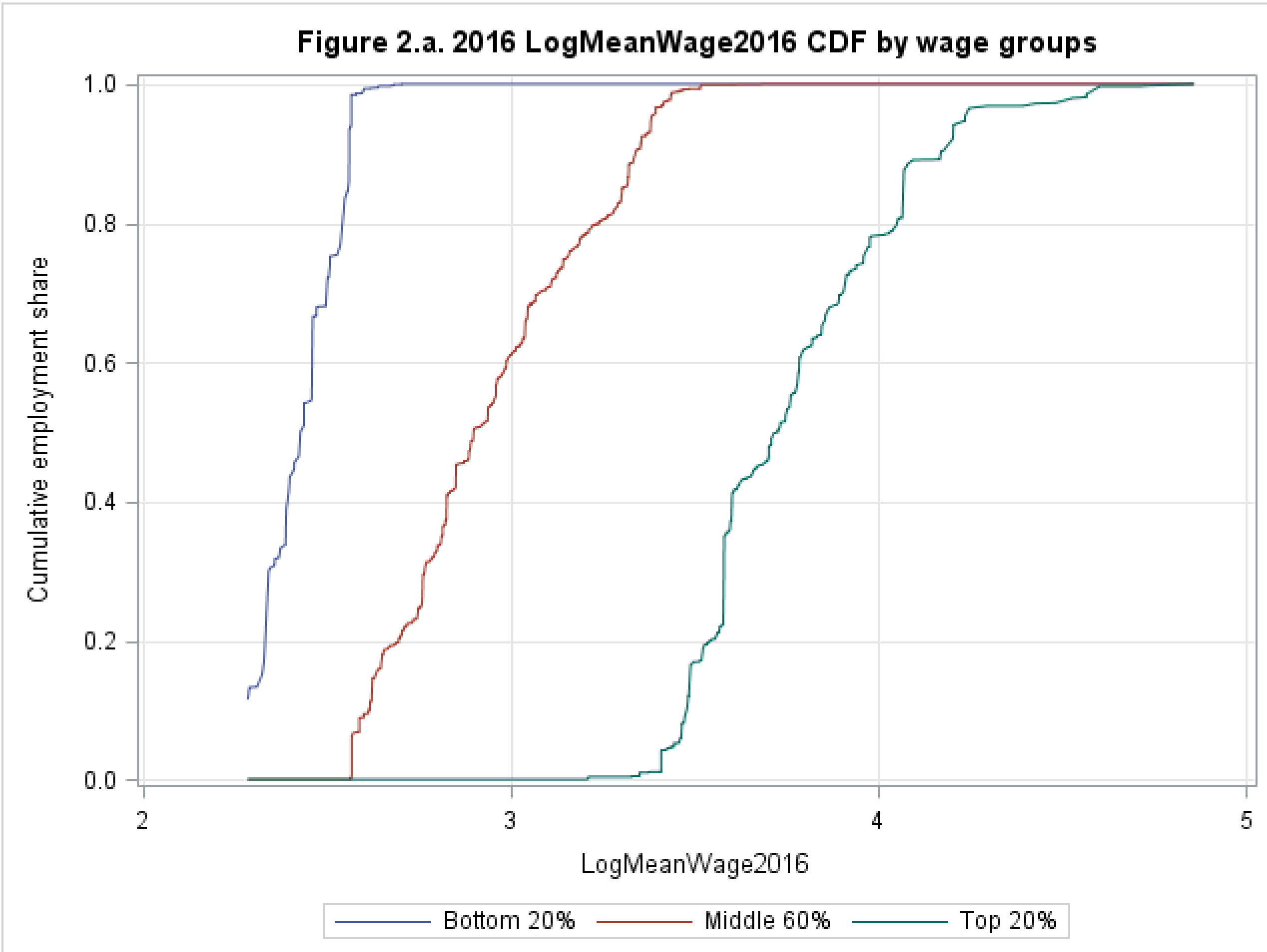


Figure 2.a. 2016 LogMeanWage2016 CDF by wage groups
1.0
0.8
0.6
0.4
0.2
0.0
Cumulative employment share
2
3
4
5
LogMeanWage2016
Bottom 20%
Middle 60%
Top 20%

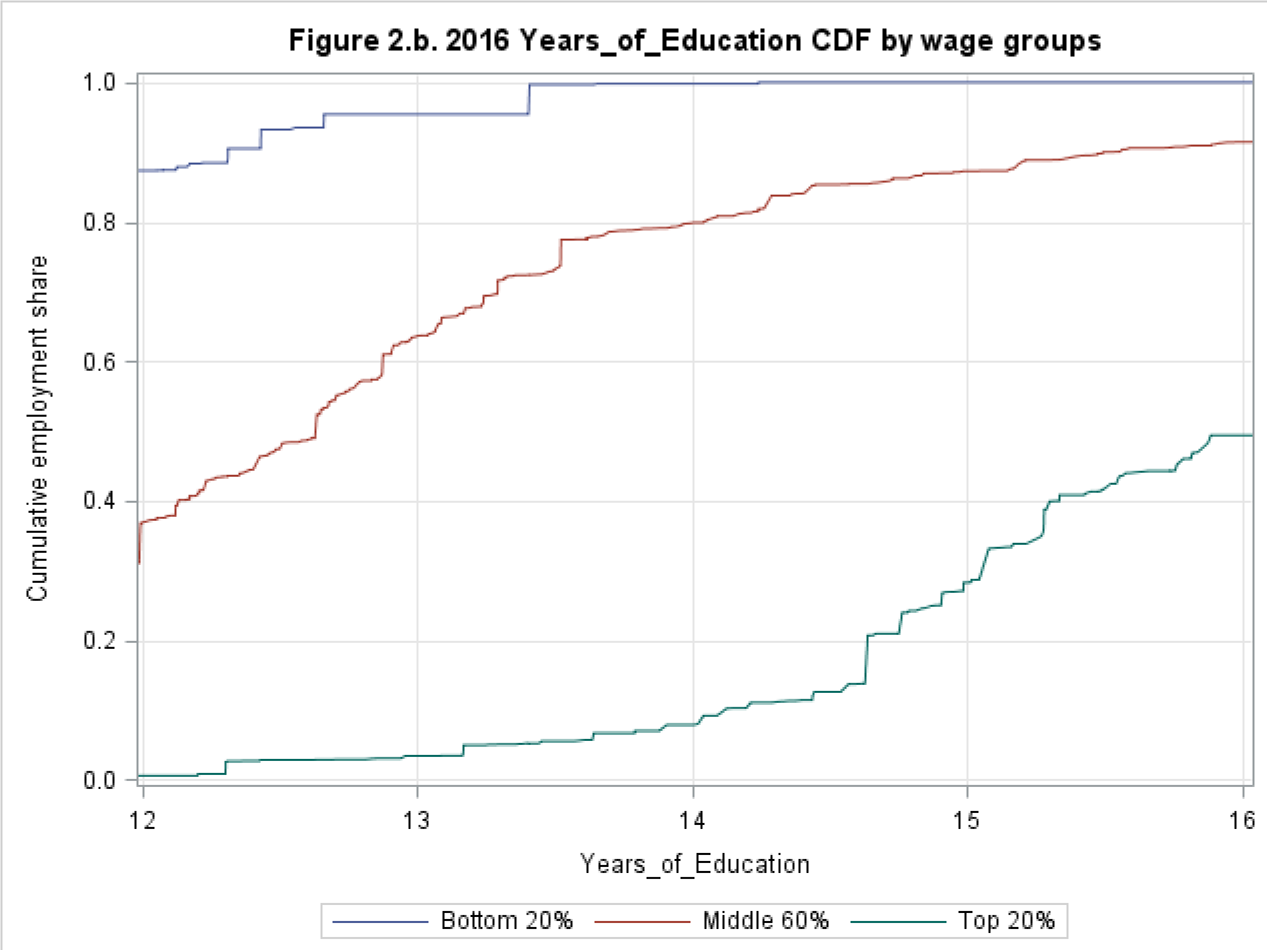


Figure 2.b. 2016 Years_of_Education CDF by wage groups
Cumulative employment share
1.0
0.8
0.6
0.4
0.2
0.0
12
13
14
15
16
Years_of_Education
Bottom 20%
Middle 60%
Top 20%

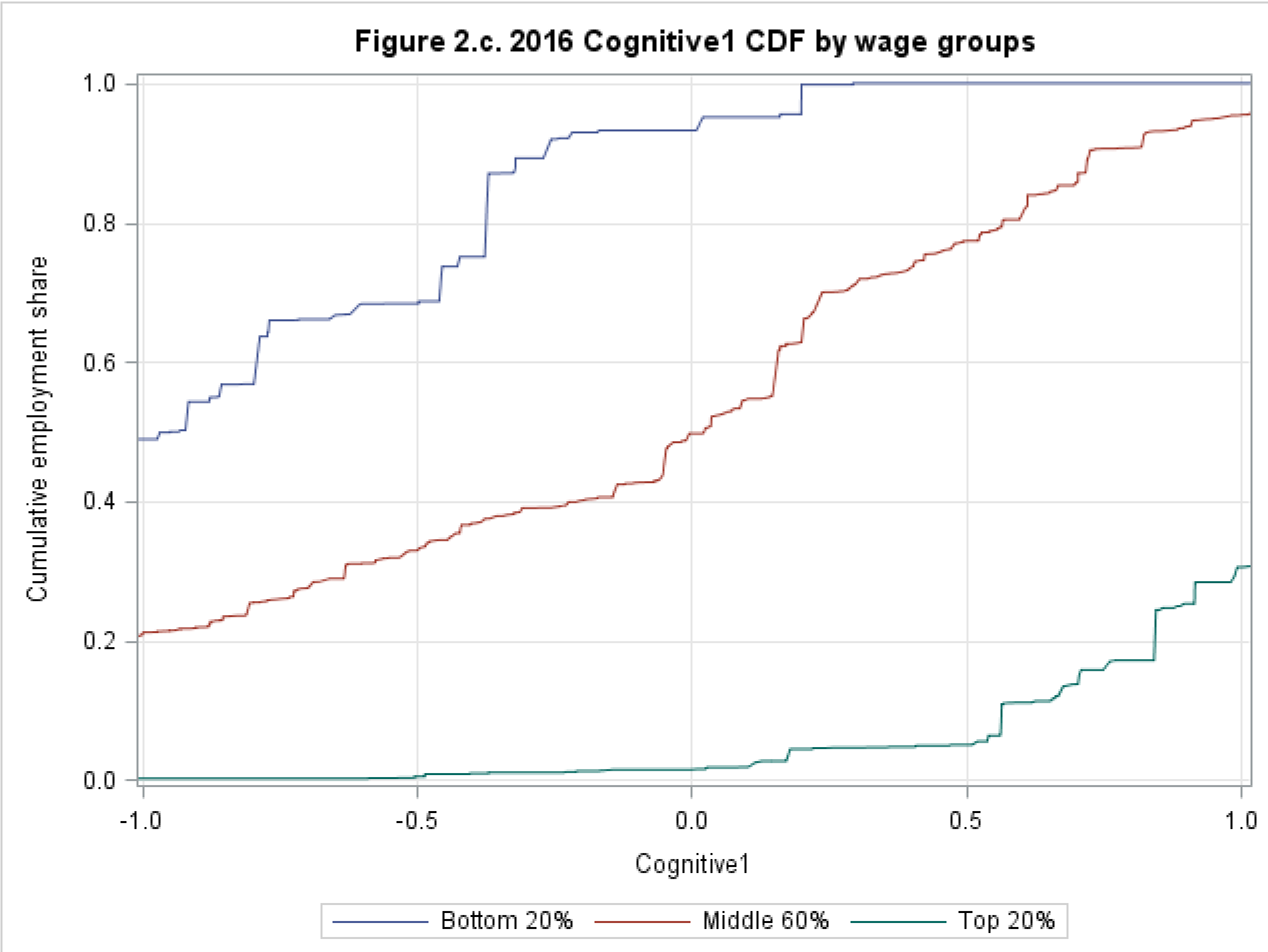


Figure 2.c. 2016 Cognitive1 CDF by wage groups
1.0
0.8
0.6
0.4
0.2
0.0
Cumulative employment share
-1.0
-0.5
0.0
0.5
1.0
Cognitive1
Bottom 20%
Middle 60%
Top 20%

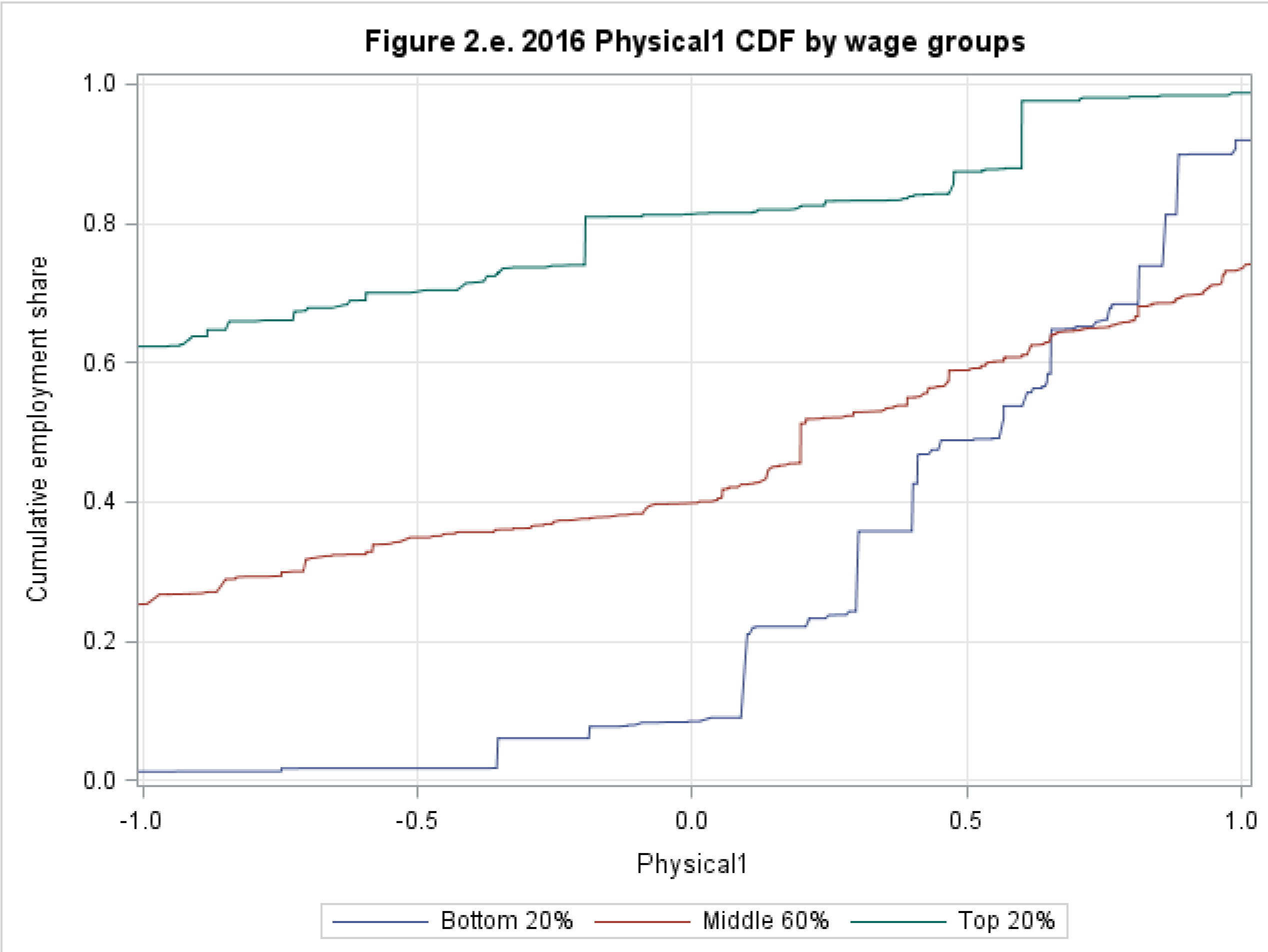


Figure 2.e. 2016 Physical1 CDF by wage groups
Cumulative employment share
0.0
0.2
0.4
0.6
0.8
1.0
-1.0
-0.5
0.0
0.5
1.0
Physical1
Bottom 20%
Middle 60%
Top 20%

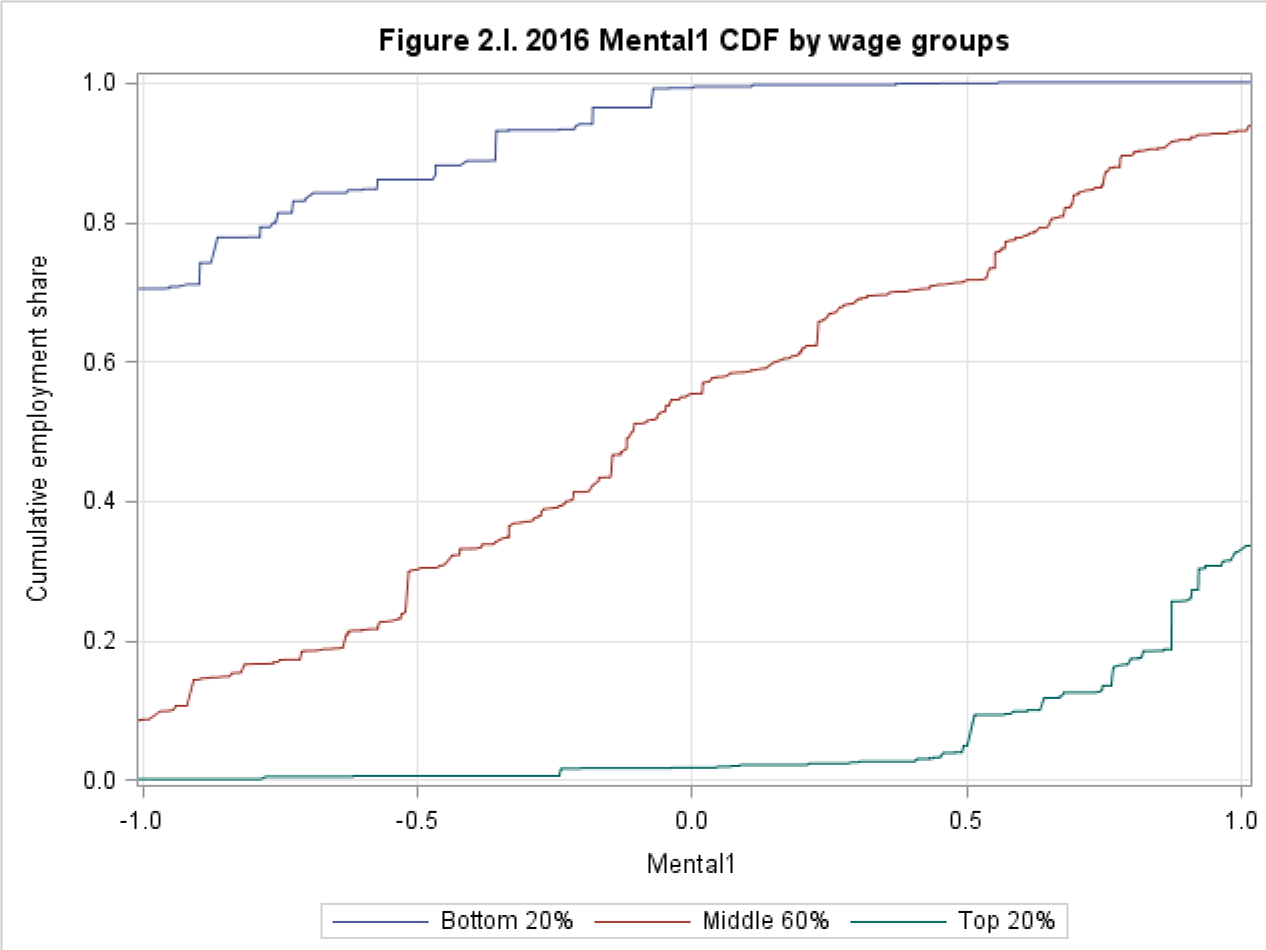


Figure 2.I. 2016 Mental1 CDF by wage groups
Cumulative employment share
1.0
0.8
0.6
0.4
0.2
0.0
-1.0
-0.5
0.0
0.5
1.0
Mental1
Bottom 20%
Middle 60%
Top 20%

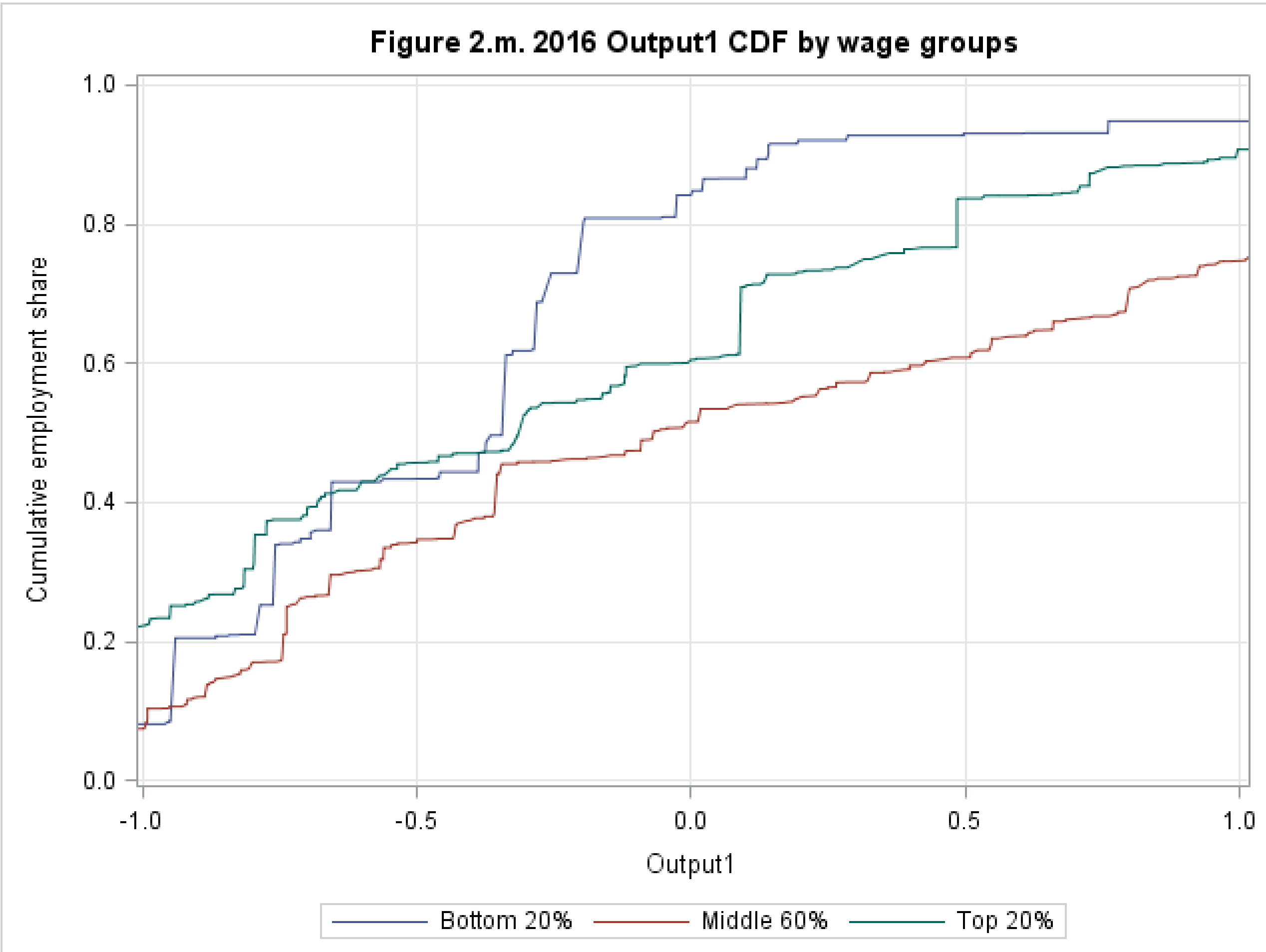


Figure 2.m. 2016 Output1 CDF by wage groups
Cumulative employment share
1.0
0.8
0.6
0.4
0.2
0.0
-1.0
-0.5
0.0
0.5
1.0
Output1
Bottom 20%
Middle 60%
Top 20%

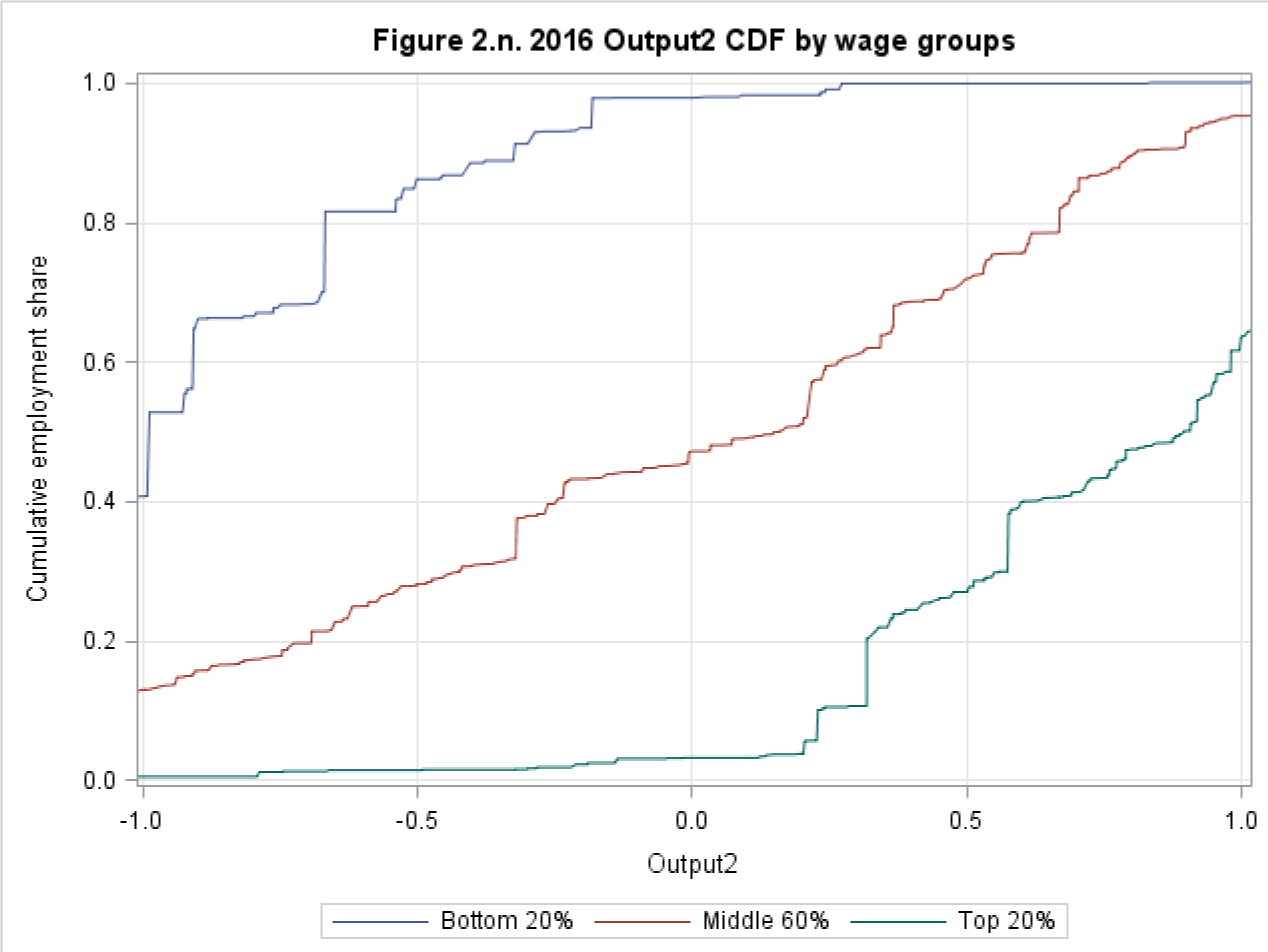


Figure 2.n. 2016 Output2 CDF by wage groups
Cumulative employment share
0.0
0.2
0.4
0.6
0.8
1.0
-1.0
-0.5
0.0
0.5
1.0
Output2
Bottom 20%
Middle 60%
Top 20%

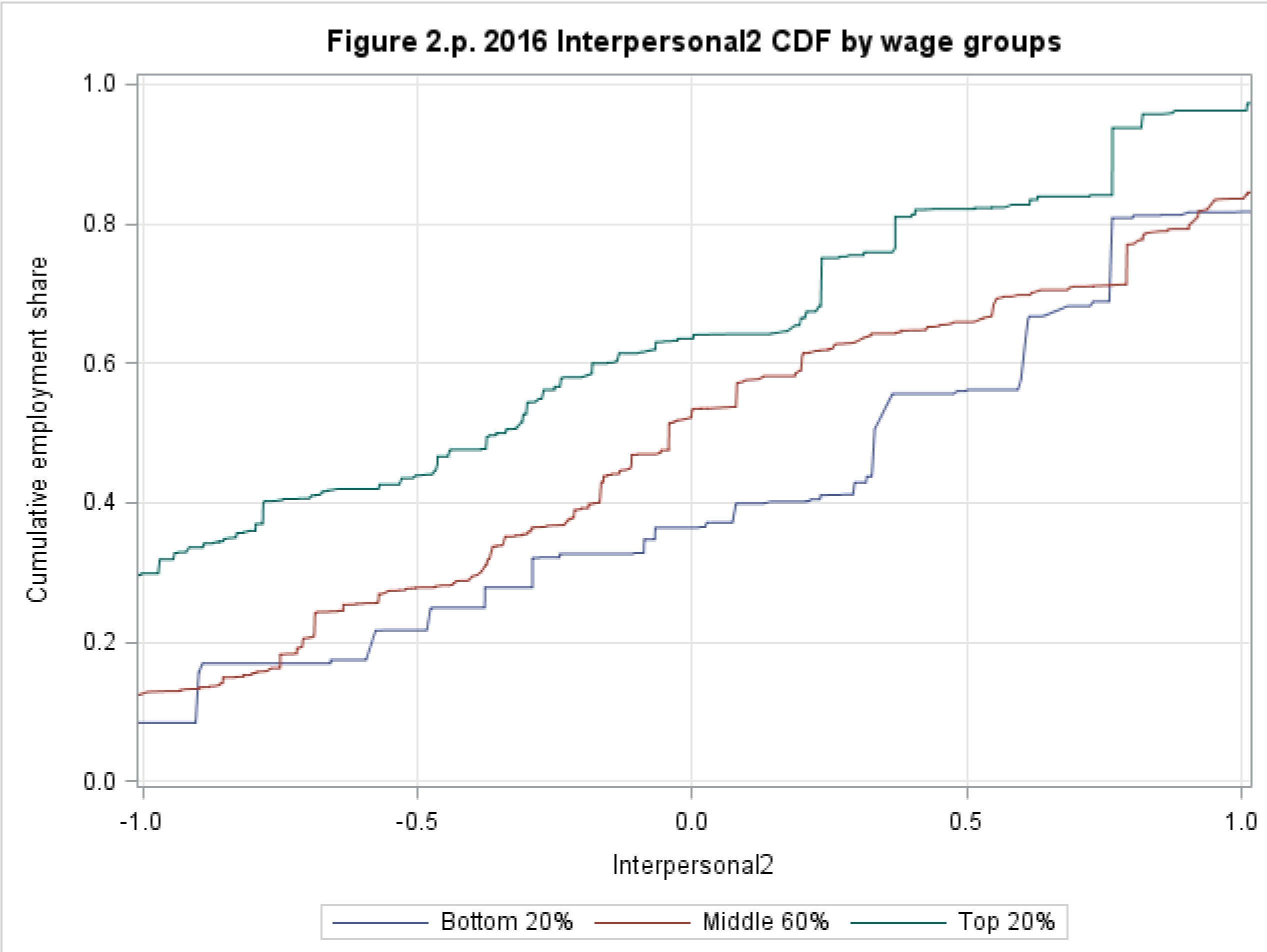


Figure 2.p. 2016 Interpersonal2 CDF by wage groups
Cumulative employment share
0.0
0.2
0.4
0.6
0.8
1.0
-1.0
-0.5
0.0
0.5
1.0
Interpersonal2
Bottom 20%
Middle 60%
Top 20%

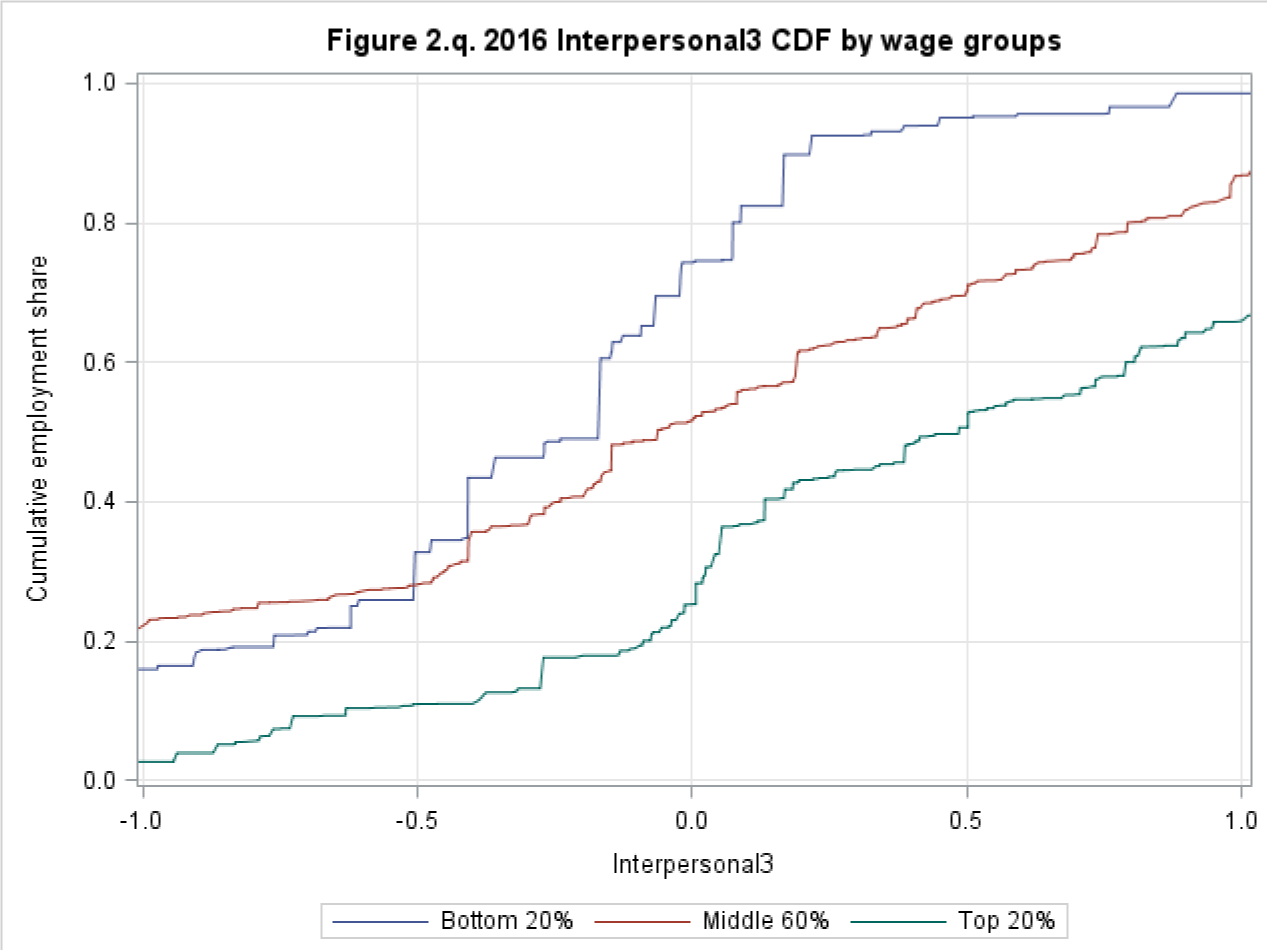


Figure 2.q. 2016 Interpersonal3 CDF by wage groups
Cumulative employment share
1.0
0.8
0.6
0.4
0.2
0.0
-1.0
-0.5
0.0
0.5
1.0
Interpersonal3
Bottom 20%
Middle 60%
Top 20%

Figure 2.r. 2016 Conditions1 CDF by wage groups

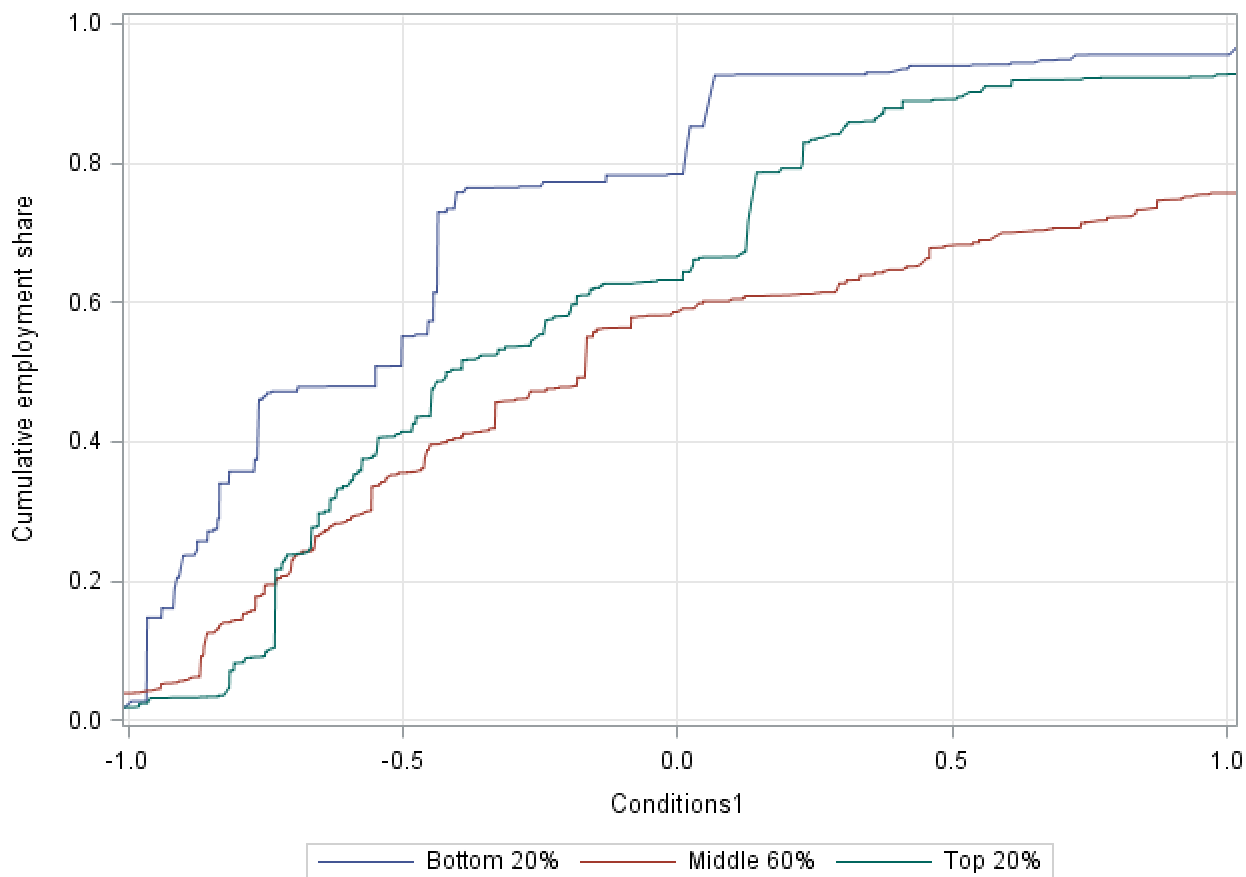


Figure 2.v. 2016 Structural1 CDF by wage groups

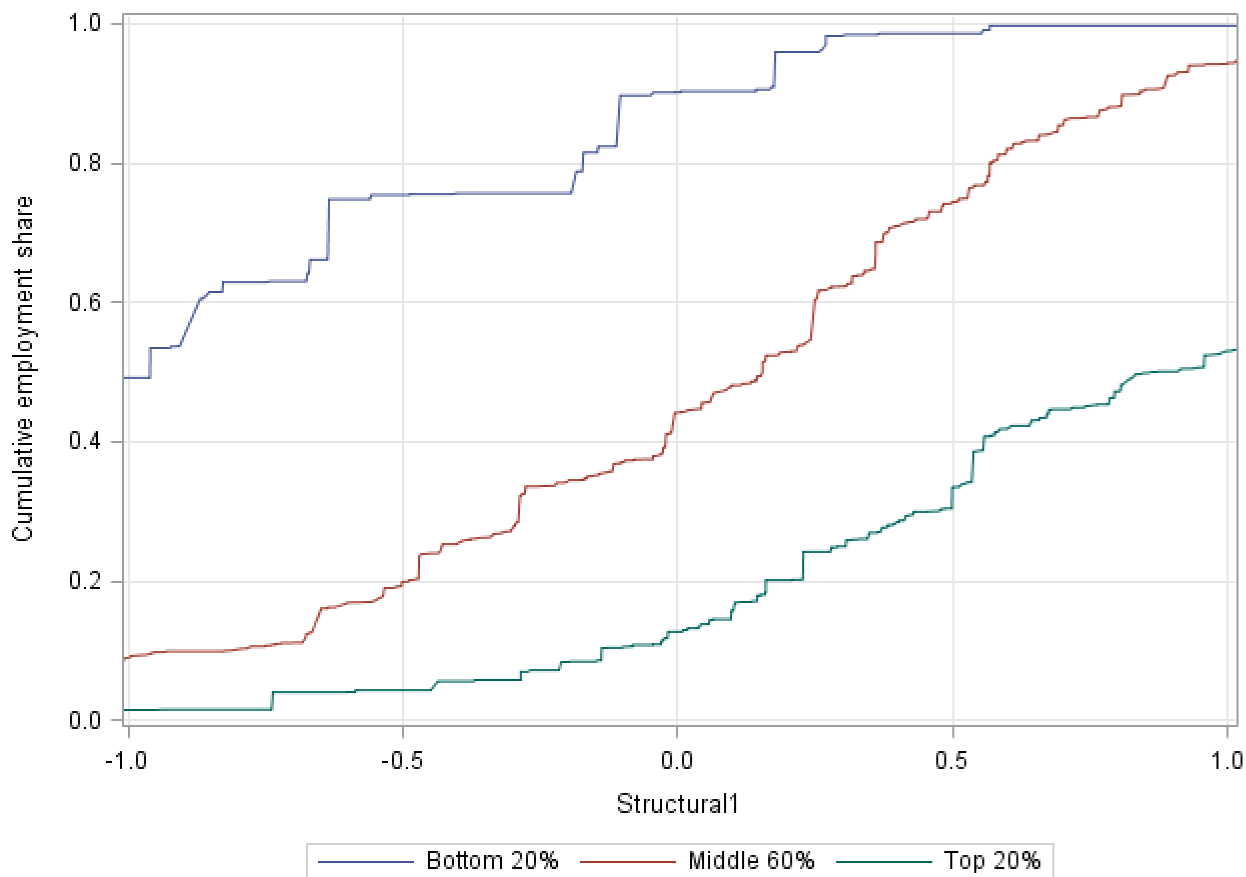
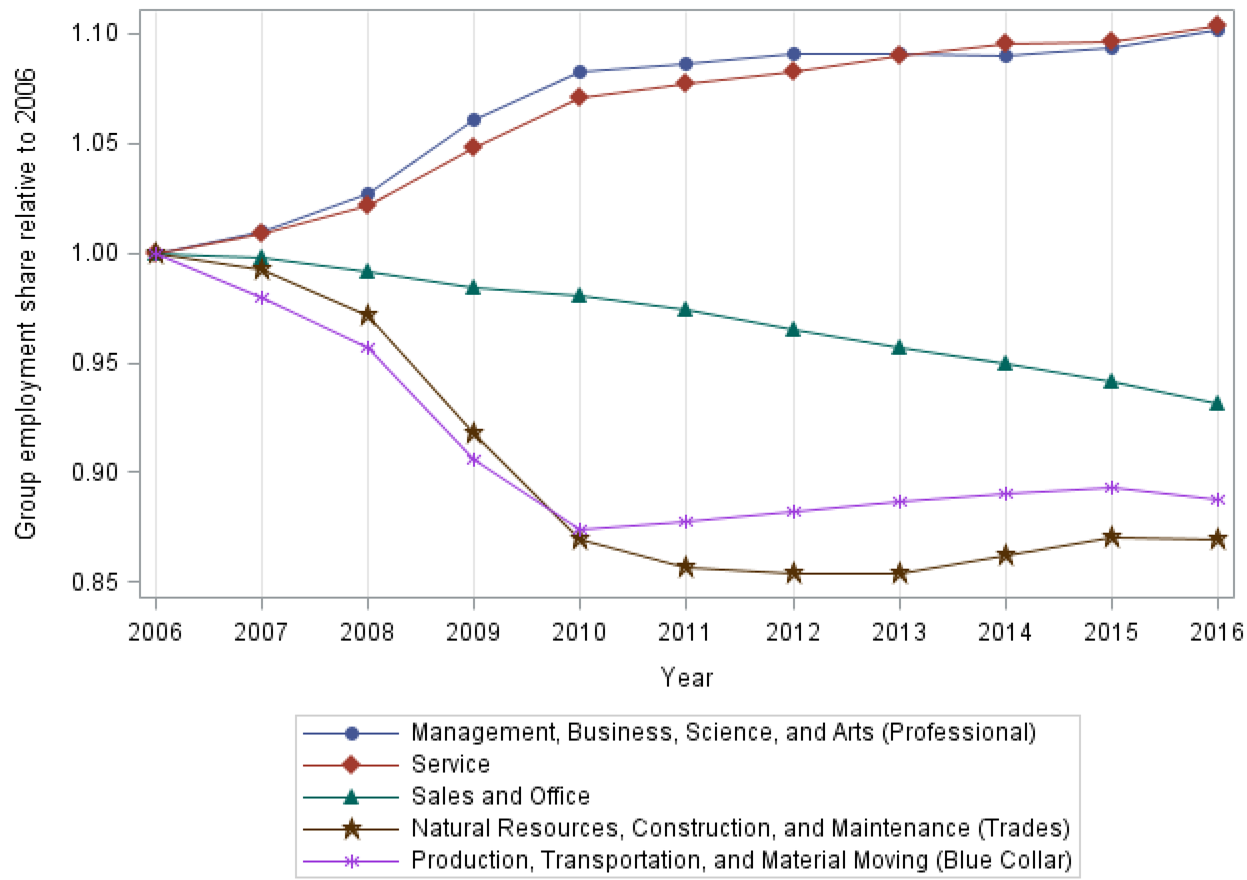


Figure 3. Evolution of aggregate occupation employment shares



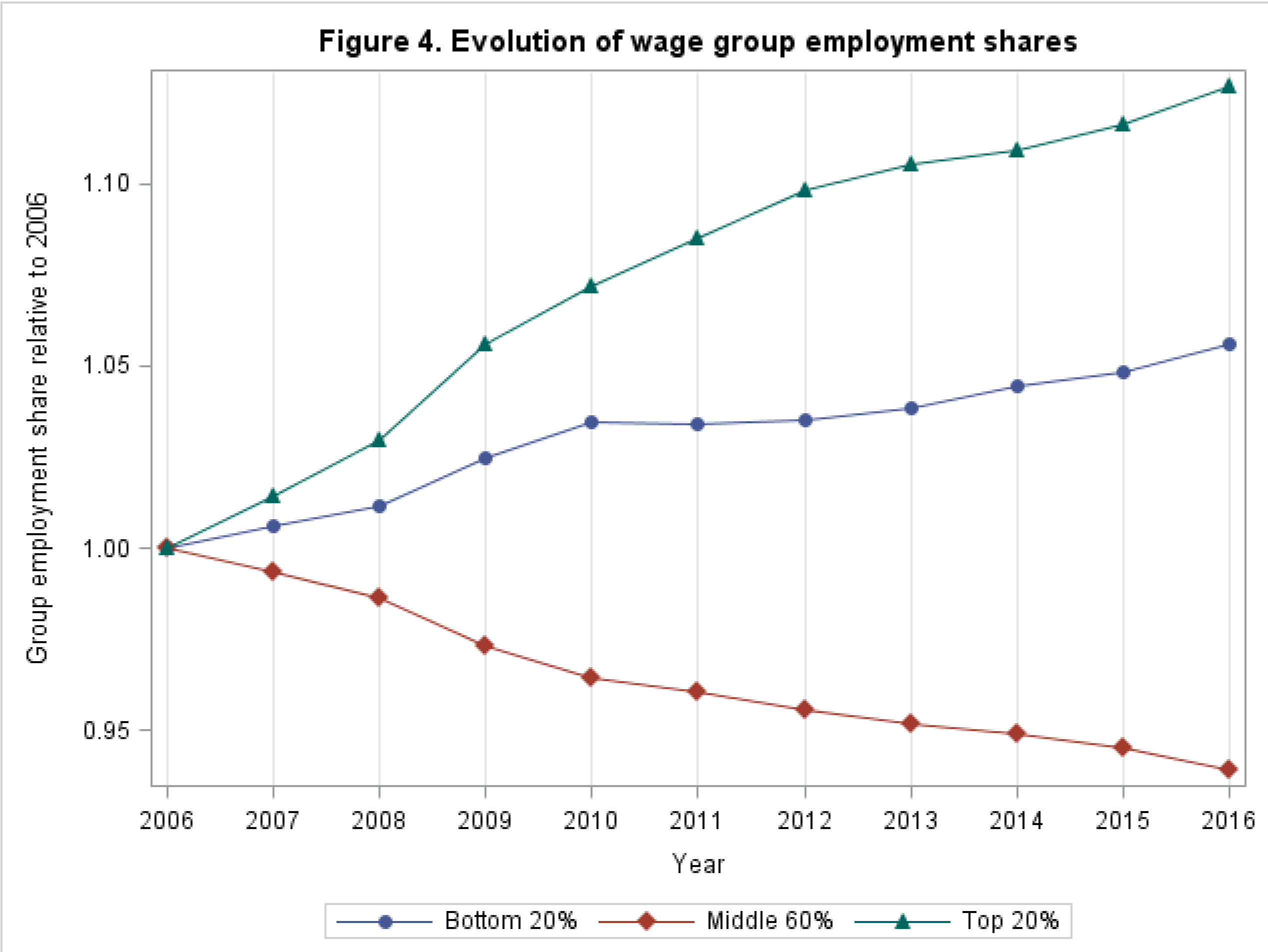


Figure 4. Evolution of wage group employment shares
Group employment share relative to 2006
1.10
1.05
1.00
0.95
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year
Bottom 20%
Middle 60%
Top 20%

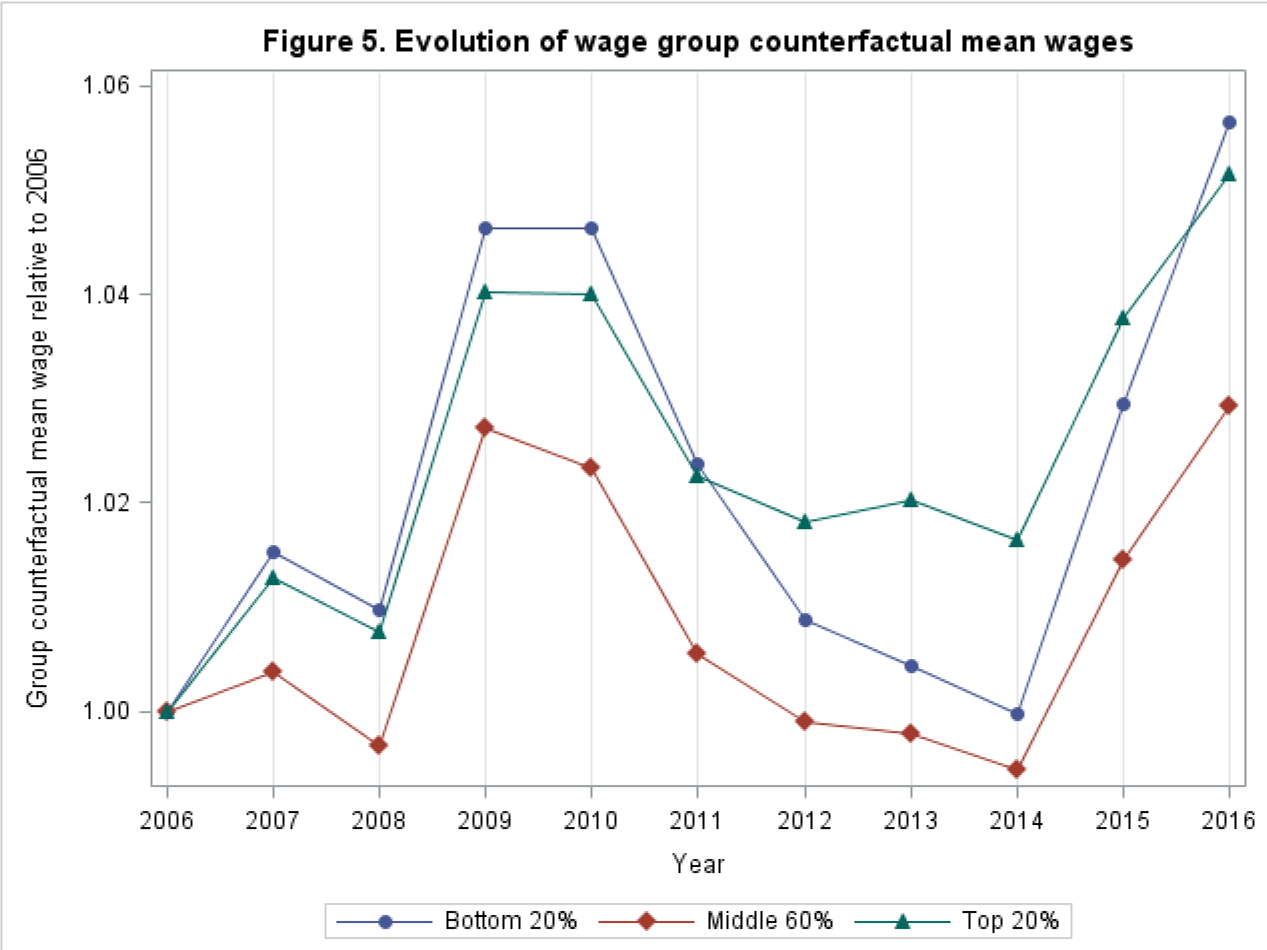


Figure 5. Evolution of wage group counterfactual mean wages
Group counterfactual mean wage relative to 2006
1.06
1.04
1.02
1.00
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year
Bottom 20%
Middle 60%
Top 20%