**Within Occupation Changes Dominate Changes in What Workers Do: A Shift-Share Decomposition, 2005-2015**

**By Richard B. Freeman, Ina Ganguli and Michael J. Handel***

The impact of technological change –particularly advances in business software, artificial intelligence (AI), and robotics – on employment and job tasks produced an explosion of media reports in the 2010s on the future of work. Despite aggregate economic statistics showing sluggish productivity growth and steady recovery in employment following the Great Recession, report after report warns that "robots or algorithms" are going to take your job (Winnick, 2018) in an outpouring of concern reminiscent of the 1960s automation scare that led President Lyndon Johnson to establish the National Commission on Technology, Automation and Economic Progress in 1964. Underlying the recent fear is the recognition that computer algorithms based on AI allow machines/robots to do intelligent tasks that once seemed solely in the domain of humans, putting a wider range of jobs at risk of automation.

The 2010s analyses of the potential effect of advanced technology on jobs differs greatly from the 1990s studies that analyzed the introduction of computers on work. Sparked in part by Frey and Osborne (2013), the current furor focuses on possible reductions in routine cognitive white-collar jobs due to computer algorithms and in blue-collar jobs due to robots and factory automation. The 1990s analysis, by contrast, estimated wage premia associated with computer use *within* jobs on the premise that computers increased cognitive skill requirements and complemented skilled and educated workers (Handel, 2007).

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This paper provides a different perspective on the possible future of work by: (1) measuring changes in job attributes/tasks from 2005 to 2015, straddling the boundary between the pre-AI and AI eras; and (2) decomposing those changes via a shift-share analysis into the changes that occurred *within occupations* and changes in the shares of employment *between occupations* with different characteristics. Per our title, the decomposition shows that most of the aggregate change in attributes/activities results from *within*-occupation changes. A key reason within changes dominate is that initial levels of the attributes that have driven much concern about the future of work – degree of automation and task repetitiveness – and other attributes of occupations, such as working in teams, are only weakly related to subsequent changes in occupational employment. While the future may differ from the past, these weak relationships cast doubt on the predictive power of projections based on changes in employment associated with occupational attributes. Micro-economic analysis of within-occupation impacts of technology may offer a better path to projecting the future of work than forecasts of changing employment levels or occupational shares, and thus a more effective guide for policies to aid workers and firms respond to the new technologies**.**

## I. Our Study and Results

Our primary source of information on job characteristics over time is the Occupational Information Network (O*NET) database developed by U.S. Department of Labor's Employment and Training Administration. While prior research has used O*NET data cross-sectionally, we create a new panel dataset that allows us to analyze changes over time for 170 job characteristics from four O*NET questionnaires completed consistently by workers (job incumbents) since 2003: *Work Context*, *Education and Training*, *Generalized Work Activities*, and *Knowledge*.[1] The

1 See Tippins and Hilton (2010) and Handel (2016) for more details about O*NET. The O*NET surveys are available at https://www.onetcenter.org/questionnaires.html. O*NET also gathers data from "occupational experts" on small occupations that

data come from samples that usually range from 20-40 workers per occupation according to a protocol designed to attain a minimum level of reliability for each occupation's scores. O*NET reports the percentage distribution of responses to items on the *Work Context* and *Education and Training* surveys, but reports only item means on the Generalized Work Activities and Knowledge surveys.

O*NET updates incumbent data on a rolling basis. Each annual release provides new information for roughly one hundred occupations and carries over older ratings for the remaining eight hundred occupations. By 2019, O*NET had rated most occupations twice, rated some once, and rated others three times, with irregular intervals between ratings. To measure changes over time for as many occupations as possible, we use O*NET files for 2008 that cover incumbent reports for 2003-2008 and files for 2018 that we restrict to incumbent reports for 2013-2018. We treat these intervals as centered on 2005 and 2015 in our shift-share analysis and use linear interpolation/extrapolation to adjust data values from nearby years to expected values for the two focal years.

We calculate job characteristics in the aggregate by weighting O*NET occupation ratings by occupational employment from the Occupational Employment Statistics (OES) for 2005 and 2015.[2] Both databases use the Standard Occupational Classification (SOC) system and thus merge easily but not completely.[3] From 2005 to 2015 O*NET's coverage of workers in SOC-level occupations declined slightly from 87.3% to 85.5% of total employment. Our sample

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are difficult to reach through sample surveys, and from professional job analysts on the *Abilities* and *Skills* questionnaires. See https://www.onetcenter.org/ db_releases.html and associated links for a full set of O*NET releases. O*NET microdata are not available. To our knowledge, only Ross (2017) has performed panel analyses using O*NET data but for different purposes than the current analysis. We discuss the data construction and robustness checks in more detail in Freeman, Ganguli and Handel (2020). Here we analyze 55 Work Context variables, 41 Education and Training variables, 66 Knowledge variables and 82 Generalized Work Activities variables (with Knowledge and Generalized Work Activities including both the Importance and Level variables).

2 See https://www.bls.gov/oes/ for description of the data and https://www.bls.gov/oes/tables.htm for data files.

3 Some SOC occupations are outside O*NET's scope. O*NET contains many occupations at a finer level of detail than the SOC. see https://www.onetcenter.org/taxonomy.html.

restrictions reduce coverage to 371 occupations, which covers 57.7% of employment in 2005 and 60.4% of employment in 2015.

The questions in the Work Context survey use a five-point scale that ask workers how *often* their current job involves some task or attribute or how *important* some kind of task or attribute is to the job, with 1 as the lowest value and 5 as the highest value. To capture high-impact changes, we report data in terms of the percentage of workers in the highest two categories, but we have also analyzed the data in terms of mean levels and obtained comparable results to those given here (see Online Appendix Table 1). The Generalized Work Activities and Knowledge surveys ask two questions about each job characteristic: "How important is _____ to your current job?" on a 1-5 scale, and "What level of _____ is needed to perform your current job?" using a 1-7 scale. We focus on the 5-point 'Importance' questions, but the 7-point 'Level' questions give similar results.

Columns 1 and 2 of Table 1 shows the average level of attributes that have received considerable attention in analyses of the future of work – the degree of automation and the repetitiveness of work, which presumptively places many human jobs at risk; control of work, and interpersonal interactions at work – and the education levels and knowledge required in an occupation. We obtain the aggregate level of an attribute by taking an employment weighted sum of the attribute for occupations in our sample and decompose the changes in Column 3 using shift-share analyses.

Formally, let $A_{ot}$ be the value of attribute A in occupation $o$ in year $t$, and $W_{ot}$ be the proportion of the workforce in $o$ in $t$, then $A_t = \Sigma W_{ot} A_{ot}$. Let $\Delta A$ be the change in the attribute over a given time period for the entire workforce, and let $\Delta A_o$ be the change over the time period for a given occupation. In this paper, the time period is 2005 to 2015.

Thus,

(1) $\Delta A = A_{2015} - A_{2005}$

(2) $\Delta A_o = A_{o2015} - A_{o2005}$.

Likewise, $\Delta W_o$ is the change in the proportion of the workforce in $o$ over the period 2005 to 2015. Thus,

(3) $\Delta W_o = W_{o2015} - W_{o2005}$.

Therefore, the decomposition of $\Delta A$ over 2005 to 2015 is:

(4) $\Delta A = \Sigma W_{o2005} \Delta A_o + \Sigma A_{o2005} \Delta W_o + \Sigma \Delta A_o \Delta W_o$,

where the first term is the contribution of *within* occupation changes (weighted by the occupation share of employment in the first year); the second term is the contribution of changes *between occupation*s (weighted by the value of A in the first year); and the last term is an interaction term that captures the residual change.

Column 3 of Table 1 shows total changes in O*NET values for these variables between 2005 and 2015. The first nine variables are measured as proportions in the highest two categories on a 1-5 scale. The values for required levels of education are also proportions. The values for variables from the *Knowledge* questionnaire are means based on the 5-point 'Importance' scales. We note two aspects of the decadal changes. First, most of the changes are modest, which suggests that if future changes follow this pattern, there will likely be ample opportunity for workers and firms to adjust to the technology. Second, some of the changes are in the opposite direction to widespread views about the future of work. The percentage of incumbents reporting that their jobs involved high levels of repetitiveness *increased* by 0.8 percentage points, contrary to predictions that repetitive jobs would be more likely to be automated, while the percentage reporting freedom to make decisions *decreased* by the equivalent of 4.7 percentage points. The percentage of workers with highly automated jobs declined, which runs counter to the fear of increasing automation (but is consistent with employment shrinking in automated occupations). Consistent with expectations, two measures of interpersonal tasks, public speaking and working with groups/teams, increased by 4.3 and 5.6 percentage points respectively. Required education level increased 1.7 percentage points for high school and 1.1 percentage points for college. The largest knowledge increase was for computer knowledge, which increased by one-quarter point on the five-point Importance scale.

The decomposition analysis in the next three columns gives us our paper title. For all 17 attributes, change *within* occupations is the main determinant of the aggregate change.[4] The within-change effect is *absolutely* larger than the "between change" from shifts in occupational employment, so that in the eight cases where the two changes move in opposite directions, the within change dominates. This includes time spent making repetitive motions and freedom at the job.

To see if the "within dominates" result is unique to our 17 variables or holds for other O*NET attributes in our database, we replicated our analysis on all 244 questions in the four O*NET surveys that queried incumbents about their work.[5] Our results generalize to the vast majority of occupational attributes, whether based on the 5-point 'Importance' or 7-point 'Level'

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[4] Appendix Table A1 shows the decomposition results for the selected Work Context variables using the means for respondents rather than the share in categories 4 and 5. The results are very similar.

[5] The 244 variables include 55 Work Context variables, 41 Education and Training variables, 66 Knowledge variables and 82 Generalized Work Activities variables (with Knowledge and Generalized Work Activities including both the Importance and Level variables).

scale: 222 of the 244 questions show a larger absolute value for the within-change than for the between-change, and when the within-change and between-change move in opposite directions, the within-change generally dominates, as it did for the attributes in Table 1.

Our results generalize beyond the O*NET data for the United States. Decomposing changes in eight work attributes in the European Working Conditions Survey, which provides data on EU-15 countries from 1995 to 2015, Bisello et al. (2019) found that within changes dominated compositional changes for 7 of the 8 attributes. The sole exception was a measure of strength at work, for which there was no within-occupation change. As in our results, they find that despite a decline of the share of jobs in occupations doing repetitive work, the overall level of repetitive work increased.

In sum, recent changes in the nature of work depended more on changes in work within occupations than on changes due to the shifting distribution of employment among occupations that underlie most projections of the likely future of work. Why have within-occupation changes dominated between-occupation shifts, and what does this mean for the plausibility of extant projections?

A significant reason for the dominance of within-occupation changes appears to be a weak relation between the change in occupational employment shares and the attributes of occupations such as high degree of automation or routine work that supposedly create "jobs at risk". Figure 1 documents this for the degree of automation using our O*NET dataset. It shows a slight negative relation between an occupation's level of automation in 2005 and the change in its share of total employment between 2005 and 2015, accounting for less than 1% of the variation in changes in employment among occupations. A similar calculation for repetitiveness shows an even weaker relation (see Table A2 and Figure A1). The contribution of between-occupation changes to aggregate changes in an attribute cannot be substantive if the correlation between the base level of the attribute and the ensuing change in employment share is small.[6]

Going beyond the degree of automation and repetitiveness, we correlated changes in occupational shares of employment from 2005 to 2015 with each of the O*NET measures of attributes from the incumbent surveys and found that the mean correlation coefficient between the 2005 level of an O*NET attribute and future change in the share of employment of an occupation was effectively zero (Freeman, Ganguli, and Handel 2020). The highest correlation between an attribute and future changes in employment shares was below 0.20, or 4% of the variance. While a principal components analysis or other function of many attributes will produce a stronger explanation of change, seeking to explain occupational change largely in terms of O*NET attributes alone does not appear promising. Many factors beyond job attributes are likely to contribute to shifts in labor demand/changes in employment: the shifting mix of production among industries with differing proportions of workers among occupations; changes in wages or other input prices, different elasticities of demand among occupations, and so on. Technological change is not the only determinant of employment and its effect can be far subtler than simply substituting machines for workers, as Bessen (2016) has noted with the impact of ATM machines on bank tellers.

Another bound on the potential magnitude of the between-occupation effect in our decomposition is that changes in occupational employment shares in the period studied were not particularly large. The correlation between employment in an occupation in 2005 and in 2015 is 0.983, and the index of dissimilarity, which measures differences in the distribution of all occupations between the two years was 0.0775. A correlation 1.00/index of dissimilarity of 0.0 would produce a zero between-change contribution to the aggregate change.

6 A zero correlation would imply the between component has no effect.

Turning to the within-occupation changes, Hu and Freeman (2020) report an increase in the number of software categories per occupation from 12.5 in 2015 to 15.8 in 2018, with 90% of the change occurring within occupations. It is possible that increased software use has altered tasks. Alternatively, the changing educational composition of the workforce, changing industry mix, more competitive product markets, monopsonistic labor markets, and changing management practices may explain within-occupation changes.

**II. Conclusion**

Finding that recent changes in job attributes and tasks were driven more by within-occupation changes in work than by the shifts in employment among occupations, that within-occupation changes were generally modest, and that the occupational attributes that underlie many projections were only weakly related to the changes in employment suggests that we should show greater skepticism toward headline projections of massive job upheaval in the foreseeable future. To gain useful insight into the future of work, analysis must go beyond projecting which occupations might grow or shrink. If we want to know how technology and other changes will impact work, we need to look at what workers do in their occupation.

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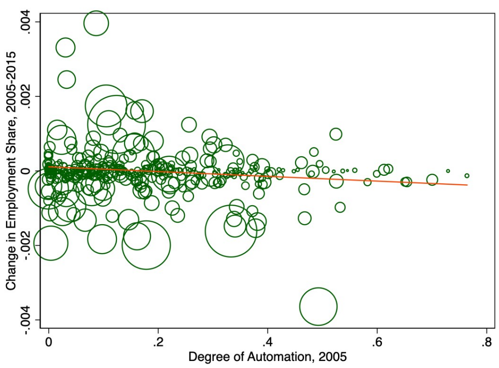
**Table 1. O*NET attributes and shift-share decomposition, 2005-2015**

| | **Share or mean** | | | **Decomposition** | | |
|---|---|---|---|---|---|---|
| | **2005** | **2015** | **Δ** | **Within** | **Between** | **Interaction** |
| **Physical Work** | | | | | | |
| (1) Degree of Automation | 0.174 | 0.143 | -0.031 | -0.029 | -0.006 | 0.003 |
| (2) Time Making Repetitive Motions | 0.479 | 0.487 | 0.008 | 0.013 | -0.006 | 0.001 |
| (3) Pace Determined by Equipment | 0.186 | 0.165 | -0.021 | -0.015 | -0.011 | 0.004 |
| (4) Time Bending or Twisting | 0.250 | 0.238 | -0.012 | -0.014 | -0.003 | 0.005 |
| **Decision latitude** | | | | | | |
| (5) Unstructured Work | 0.700 | 0.692 | -0.008 | -0.008 | 0.004 | -0.005 |
| (6) Freedom to Make Decisions | 0.715 | 0.668 | -0.047 | -0.045 | 0.005 | -0.006 |
| **Social Skills** | | | | | | |
| (7) Public Speaking | 0.143 | 0.187 | 0.043 | 0.041 | -0.001 | 0.003 |
| (8) Face-to-Face Discussions | 0.849 | 0.864 | 0.015 | 0.016 | 0.001 | -0.002 |
| (9) Work With Group or Team | 0.742 | 0.798 | 0.056 | 0.053 | 0.007 | -0.004 |
| ***Required Level of Education*** | | | | | | |
| (10) High School Diploma | 0.389 | 0.406 | 0.017 | 0.025 | -0.008 | 0.001 |
| (11) Associate's Degree | 0.071 | 0.074 | 0.003 | 0.005 | -0.002 | 0.000 |

| | | | | | | |
|---|---|---|---|---|---|---|
| (12) Bachelor's Degree | 0.124 | 0.134 | 0.011 | 0.009 | 0.001 | 0.001 |
| (13) Master's Degree | 0.027 | 0.035 | 0.007 | 0.005 | 0.002 | 0.000 |
| ***Knowledge*** (mean, 1-5 scale) | | | | | | |
| (14) Administration and Management | 2.845 | 2.929 | 0.084 | 0.064 | 0.001 | 0.019 |
| (15) Computers and Electronics | 2.526 | 2.767 | 0.241 | 0.235 | -0.012 | 0.018 |
| (16) Mechanical | 2.006 | 2.02 | 0.015 | 0.023 | -0.008 | -0.001 |
| (17) Mathematics | 2.967 | 2.92 | -0.047 | -0.054 | -0.002 | 0.009 |

Notes: Variables in lines 1-9 are measured on 5-point scales; values for 2005 and 2015 are the average proportion of respondents in the top two categories (4 or 5) across all occupations in our sample. Values for 2005 and 2015 in lines 10-13 are the average proportions reporting that education level is required to be hired for their job. Variables in lines 14-17 are measured on a 5-point Importance scale (1=Not Important, 5=Extremely Important); values for 2005 and 2015 are the average of occupation-level means across all occupations in our sample. All proportions and means are weighted by occupational employment in 2005 or 2015. Δ is the change in the average proportion or mean from 2005 to 2015.

## Figure 1: The Weak Relation Between Automation and Change in an Occupation's Employment Share




Notes:

Circles represent 371 occupations. The x-axis is the proportion of respondents in the top two categories (4 or 5) of the degree of automation question ("how automated is your current job?") for 2005 (4 = highly automated, 5 = completely automated). Thus, a value of 0.4 means that 40 percent of the incumbents surveyed in the occupation reported either a 4 or a 5 for this item. The y-axis is the change in the share of employment in each occupation from 2005 to 2015, measured in percentage points. Thus, the occupation with the largest value of 0.004 increased its share of employment by four-tenths of a percentage point.