Identifying the Multiple Skills in Skill-Biased Technical Change

Seth Gordon Benzell*
Erik Brynjolfsson†
Frank MacCrory‡
George Westerman§

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Abstract

We use an unsupervised machine learning technique, iterated exploratory factor analysis, to characterize occupations by the importance of eight endogenously derived orthogonal skills. These factors have clear interpretations and intuitive relationships to the wage distribution. We measure the relationship of each of these factors to wage and employment growth, directly and as mediated by IT usage. Leadership intensive occupations saw significant increases in both wages and employment. Physically intensive occupations saw significant decreases in occupational wages, and cooperation intensive occupations saw employment growth. The increase in leadership intensive occupational wages and decrease in physically intensive occupational wages is more pronounced for occupations and industries that use IT capital more intensely. We contrast our results for leadership and cooperation skills with those from Deming (2017) on the growing importance of social skills. We provide evidence that wage and employment growth in social skill intensive occupations nests two distinct trends. The first is an increase in wages for *leadership*-intensive occupations concentrated in occupations and industries with *high* IT capital intensity. The latter is an increase in employment for *cooperation*-intensive occupations concentrated in occupations and industries with *low* IT capital intensity.

*MIT. Email: sbenzell@mit.edu.
†MIT and NBER
‡Fordham University, Gabelli School of Business
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1 Introduction

"It is not enough to be industrious; so are the ants. What are you industrious about?"

Henry David Thoreau

Epochal changes in the US occupational wage and employment distribution have taken place over the last forty years. As documented by Autor and Dorn (2013), among others, these changes have tended to polarize employment and wages. A common explanation for these changes in the wage distribution is skill-biased technological changes (SBTC). Under this theory, occupations with weak employment and wage growth are those which are substitutes for, rather than complements to, new technologies.

An important limitation of these papers is their reliance on arbitrarily constructed skill indexes. Studies of this type typically identify a single occupational characteristic of interest, routineness for example, and measure it using a loosely motivated and ad-hoc measure. This limits the ability of these papers to identify precisely how skills interact with technological change. In this paper, we use a standard social science unsupervised machine learning technique for dimensionality reduction, iterated exploratory factor analysis, to generate a characterization of US occupations. These factors have clear interpretations and intuitive relationships to the wage distribution. The eight factors we identify are well characterized as physical, technical operation, perception, leadership, cooperation, initiative, mathematics, and education skill intensities.

We next evaluate how occupations of different types have seen their wages and employment evolve over the last decade. We find that physically intensive occupations saw significant decreases in occupational wage, while leadership intensive occupations saw significant increases in wage and employment. Cooperative occupations saw increases in employment, especially in non-routine occupations, but no additional wage growth. The increase in leadership intensive occupational wage and relative decrease in physical intensive occupational wage is more important for occupations and industries that use computers and IT capital (ITC) more intensely. This is consistent with changes in relative demand for these skills due to ITC deepening. The increase in employment for cooperation intensive occupations is focused in occupations and industries that use ITC less intensely. This is consistent with industries and occupations that have been less impacted by technology providing refuge for cooperative workers who have seen their previous positions automated.

Our cooperation and leadership measures are reminiscent of the 'social skills' found to be important to labor demand shifts in previous research. In the final section of our paper, we juxtapose our measures of social skills against those in Deming (2017). While our leadership and cooperation are orthogonal by construction, both are correlated with Deming's measure of social skill. Including this measure in regressions explaining occupational wage and employment change, leadership and cooperation's effects remain large and significant, while socialness enters approximately neutrally. LASSO regressions confirm this result and provide further evidence that wage growth is concentrated in occupations requiring management skills and employment growth is concentrated in occupations requiring empathetic skills. The fact that Deming's findings from his social skill index combine elements of these two underlying trends illustrates the importance of using skill measures that emerge organically from the data, rather than imposed a-priori.

2 Background

What is technology's role in shifting labor demand? Early studies of SBTC focused on the wage premium for high-skilled individuals. The share of workers with a high school or college education increased dramatically in the latter half of the 20th century. Yet, across nations, the wage premium for the educated stayed constant or increased over this interval (Berman et al., 1998). This is consistent with high-skilled individuals being disproportionately favored by technological change. High-skill individuals are typically defined as those with college degrees (such as in the capital skill complementarity literature, see for example Krusell et al. (2000)) and high-skill occupations as those with high wages at the beginning of the period under consideration.

There is also theoretical and empirical evidence of technology playing a role in the rise of the 1%'s share of income. The increase in top income shares has impacted top earners in all industries Kaplan and Rauh (2013). The increasing income of superstar workers is due to their increasing importance in output, and likely contributes to stagnant median wages, low interest rates, and slow economic growth (Benzell and Brynjolfsson, 2019). Rosen (1981) presciently forecasted that economies of scale enabled by new technologies would increase inequality. Innovations in, for example, telecommunications lead more tasks to be winner-take-all where gains might have been more evenly distributed in the past. Rosen only speculates on which types of tasks these are. One contribution of our paper is to identify which occupational characteristics see skewed returns due to information technologies.

More recent papers have diagnosed labor demand *polarization* as a consequence of technological change. From 1980 to 2005, occupations which were highly compensated in 1980 saw disproportionate growth in both wage and employment. The same is true of occupations compensated poorly. Other occupations saw little employment or wage growth. Autor and Dorn (2013) find that areas that specialized historically in industries which use routine tasks intensively (such as manufacturing) saw larger increases in wage and employment polarization. This finding remains after controlling for the offshorability of jobs. They follow Autor et al. (2003) in attributing this to technological advances, in particular information technology, which tend to substitute for people in routine jobs. Each of these papers uses indexes of occupational characteristics to characterize occupations as routine or non-routine. Other papers looking at the role of technological change in wage polarization in developed countries are Acemoglu (1999), Goos and Manning (2007), and Goos et al. (2010, 2014).

Other papers have tracked employment changes in more precisely conceptually defined skill groups. However, they also have used loosely motivated and ad-hoc occupational task intensity measures. Typically they are constructed as averages of a handful of occupational characteristic scores from a government occupational classification system. The two most commonly used for this purpose are the US's Dictionary of Occupational Titles (DOT) or Occupational Information Network (O*NET).

There are many examples of papers in this vein. For example, Acemoglu and Autor (2011) propose five measures: non-routine cognitive-analytical, non-routine cognitive-interpersonal, routine-cognitive, routine-manual, non-routine manual-physical, and offshorability. Each is an index of three to seven normalized O*NET occupational characteristic scores. Deming (2017) measures the social skill and cognitive level of occupations using an index of O*NET characteristics and individual social orientation using an index of NLSY survey questions. It finds evidence that returns to social skills have increased in the US, especially for occupations that require a high degree of both social and cognitive skill. In Deming and Kahn (2018) the authors find additional evidence of returns to skills at the job rather than occupation level. The authors hand-sort a list of words that commonly appear in job postings into one of ten non-exhaustive skill categories. Both within and across occupations they find jobs requiring cognitive and social skills demand higher wages, and they additionally find evidence of complementarity between these skills.

While the indexes constructed in this manner are certainly interesting, their undisciplined construction is problematic. They raise the concern that results may be sensitive to arbitrary changes. An arbitrarily constructed index is one that may have been subconsciously selected so as to generate exciting results. One example of potentially important arbitrariness is in the definition of routine tasks in Autor and Dorn (2013). Following Autor, Katz, and Kearny (2006) they measure the routineness, abstractness, and manualness of a task each as the average of two DOT measures. Routine corresponds to the average of "set limits, tolerances and standards," and "finger dexterity." Abstract is the average of two other measures: "direction, control and planning" and "GED math." The 'manual' measure reproduces the DOT measure "eye-hand-foot coordination". They then define a summary measure of occupational routineness. This is the log of routineness less the log of abstractness and manualness. Consider a pair of occupations where the second is twice as high as the first in all of these measures. It would be measured as much less routine than the first, despite scoring much higher in routineness. This seems a counterintuitive result, even setting aside the loose connection between the intermediate concepts and the underlying measures.

Our paper improves on this literature by building occupational characteristic measures using a well understood unsupervised machine learning technique for dimensionality reduction. For raw data, we use over 100 raw occupational characteristic scores from O*NET. The occupational characterization produced by this procedure has eight dimensions. They are well described as corresponding to the physical, technical operation, perception, leadership, cooperation, initiative, mathematics, and education task intensity of an occupation. Notably, some characterizations of an occupation many consider important, such as routineness, are absent from this list, while others, like social skill intensity, are captured by two or more factors.

Since the first draft of this paper was circulated in 2014, there has been at least one other paper published which characterizes occupational skill intensities using O*NET data and unsupervised machine learning techniques. Alabulkareem, Frank, Sun, AlShebli, Hidalgo, and Rahwan (2018) first normalize O*NET occupational skill intensity scores using revealed comparative advantage (RCA). They then use these occupation and O*NET element specific RCA scores. The complementary of a pair of skills is measured as the minimum of the conditional probabilities of a pair of skills being used by the same occupation. Complementary clusters between pairs of skills is found to reveal a bimodal distribution. Using this distribution, occupations are characterized as more or less socio-cognitive. The paper proceeds to juxtapose occupations with higher and lower scores under this one-dimensional measure. The authors show that more socio-cognitive occupations have higher wages, even after controlling for routineness and education level. They also show that connections between occupational skill usages between occupations predict occupational mobility between these occupations.

3 Data and Skill Measurement

We draw our civilian employment and wage figures from the Bureau of Labor Statistics' Occupational Employment Survey (OES), using the annual statistics published at www.bls.gov/oes through year 2016. For each occupation, the OES reports employment, average wage, and median wage by industry. Our main result are on employment and median hourly wages.[1]

Our underlying skill data is derived from the Department of Labor's O*NET dataset (available at www.onetcenter.org). This database provides empirical data on the content of occupations in the US economy. It includes information about characteristics of the job itself (e.g. its typical tasks, level of responsibility, and exposure to hazards) as well as on the people who perform the job (e.g. their abilities, skills, and interests).

Our analysis begins with O*NET's evaluation of the importance of four categories of occupational characteristics: Abilities (1.a), Work Activities (4.a), Skills (2.a and 2.b) and Work Styles (1.c). This encompases all O*NET importance measures except those categorized as Knowledge (2.c). The 142 elements meeting these criteria reflect highly trained labor experts' assessments of the importance of each skill to each occupation. We focus on occupational characteristics in a base year due to a concern that rankings are incomparable across years.[2] The Standard Occupation Code system was updated in 2006, by which

[1] All wages are deflated to constant 2006 dollars using the January Consumer Price Index for all urban households (CPI-U) published at www.bls.gov/cpi.

[2] Up until 2007, skill data was collected primarily from incumbents employed in the focal

time virtually all occupations in O*NET had Work Style ratings. We therefore chose the December 2006 O*NET release for all occupation characteristics. After cleaning, O*NET has 798 scored occupations in 2006.

We use iterated exploratory factor analysis, an unsupervised machine learning technique, to summarize occupations by their skill intensity along several dimensions. The procedure begins by performing a principal-component factoring of the importance scores for retained O*NET questions across occupations. Orthogonal varimax rotation is then applied to the loading matrix. This rotation maximizes the variance of the squared loadings within factors, while making sure all factors are orthogonal. Subsequently, any O*NET score with a loading with an absolute value of less than .5 in all factors is discarded. Any O*NET score with a weighing of more than .4 in at least two factors is also discarded. After these criteria are implemented, the process is repeated, now with a minimum loading of .51 (the maximum cross loading remains fixed at .4 threshold). The procedure is iterated until the minimum loading reaches .7. This procedure creates several orthogonal factors, with each retained O*NET characteristic contributing primarily to one and only one factor. The iterated nature of raising the threshold allows us to exclude cross-loading items without dropping important items due to correlation with unimportant items. This tool has been used for dimensionality reduction in many previous social science contexts. The specific procedure we utilize, i.e. the .7 minimum factor loading and .4 maximum cross loading, follows (Hair et al., 2013) (page 114). This cutoff ensures that the factor analysis has a well defined structure.

Eight readily understandable factors are retained which summarize the occupation. These factors are listed from most to least important in terms of explaining variation in occupations' O*NET scores. Alongside are listed their primiary constituent O*NET characteristics.

- **Physicality (PHYS):** Arm-Hand Steadiness; Multilimb Coordination; Static Strength; Dynamic Strength; Trunk Strength; Stamina; Extent Flexibility; Gross Body Coordination; Gross Body Equilibrium; Performing General Physical Activities; Handling and Moving Objects; Manual Dexterity

- **Technical Sophistication (TECH):** Repairing and Maintaining Electronic Equipment; Technology Design; Equipment Selection; Installation;

professions. Updates from 2008 onward collect skill data from labor analysts.

Operation Monitoring; Operation and Control; Troubleshooting; Quality Control Analysis; Systems Analysis

- **Perception (PERC):** Speed of Closure; Flexibility of Closure; Perceptual Speed; Selective Attention; Far Vision; Hearing Sensitivity; Auditory Attention
- **Leadership (LEAD):** Scheduling Work and Activities; Coordinating the Work and Activities of Others; Developing and Building Teams; Guiding, Directing, and Motivating Subordinates; Staffing Organizational Units; Monitoring and Controlling Resources
- **Cooperation (COOP):** Cooperation; Concern for Others; Social Orientation; Self Control; Stress Tolerance
- **Initiative (INIT):** Achievement/Effort; Persistence; Initiative; Independence; Innovation
- **Mathematics (MATH):** Number Facility; Mathematical Reasoning; Mathematics
- **Teaching and Education (EDUC):** Learning Strategies; Instructing

Although we invented names for each of these factors, each factor's contents and the total number of factors are derived directly from the raw data. Note that while the above lists the most important characteristics within each factor (i.e. those with loadings of more than .7), all factors are a function of all retained O*NET elements. However, because all elements with cross-loadings of more than .5 are eliminated, non-primary elements contribute relatively little to an occupation's factor score.

After generating scores for the different skill intensities of different occupations, the data are merged with BLS employment data. BLS employment data are used at the occupation-three digit industry-year level. While the two sources use very similar employment categorizations, a difficulty arises from the fact that O*NET uses a finer level of granularity than BLS. For example, O*NET lists seven kinds of employment officers, while BLS has only one type. For BLS occupations that correspond to more than one O*NET occupation, we take the raw average of the O*NET occupation factor scores when merging into BLS data.

Table 1: Occupational characteristic scores for occupations of interest.

	PHYS	TECH	PERC	LEAD	COOP	INIT	MATH	EDUC
Dish Washer	0.75	0.11	-0.78	-0.15	-0.62	-1.76	-1.08	0.06
Chief Executive	-0.80	0.57	-0.82	1.67	0.94	1.04	1.82	-0.26
Landscape Architect	-0.95	-0.83	0.79	2.00	-2.10	-0.40	0.17	-1.10
Policeman	1.24	-0.65	1.49	0.30	0.88	1.03	-0.64	0.24
Detective	0.54	-0.39	1.44	-0.33	0.21	0.57	-0.28	0.78
Chemist	-0.74	2.12	-0.89	-1.35	-0.51	1.06	0.19	0.09
Economist	-1.32	-0.82	-0.51	-0.33	-1.32	1.00	1.65	-0.57

Table 2: Occupational characteristic score percentiles for occupations of interest.

	PHYS	TECH	PERC	LEAD	COOP	INIT	MATH	EDUC
Dish Washer	67.7	77.5	32.3	58.2	15.0	7.8	13.4	77.3
Chief Executive	25.5	85.4	30.4	94.0	73.7	93.8	92.5	58.5
Landscape Architect	19.0	37.0	86.4	96.3	.3	42.3	47.1	17.4
Policeman	86.7	40.7	96.8	73.7	70.5	93.1	24.5	81.9
Detective	56.8	57.0	96.7	50.0	42.9	82.8	34.8	90.9
Chemist	26.9	99.6	27.5	10.7	17.4	94.0	47.2	78.5
Economist	3.1	37.1	42.0	50.1	4.0	92.9	87.1	38.5

A final source of data used for this analysis is on the use of information and technology capital by industry. Our industry IT capital intensity measure is from the BEA current-cost net capital stock of private nonresidential fixed assets.[3] We define the ITC intensity of an industry as the ratio of ITC capital to the current total capital stock. The types of capital considered ITC are: Computers, mainframes and accessories (EP1), software (ENS), communications equipment (EP2) and communications structures (SU2). The BEA reports the capital stock for most industries at the three digit level. However, for a large subset of industries for which we have BLS data, the BEA data is at a higher level of aggregation (i.e. the total capital stock for a pair of three-digit NAICS industries is reported together). In our main analysis, we assign the same ITC intensity to sets of industries that are combined in the BEA data.

After this last addition we drop from the data occupation-industry pairs without median wage or employment data in 2006 or 2016. These restrictions produce a final data set with 88 industries and 537 occupations for analysis.

Table 1 gives factor scores for several occupations of interest. Table 2 gives employment weighted percentiles. Dishwasher and CEO are among the highest and lowest compensated occupations respectively. Physical skill is slightly more important for dishwashers than the average occupation, but the position requires

[3]Retrieved from https://apps.bea.gov/national/FA2004/Details/Index.htm.

few other skills in abundance. CEOs, on the other hand, need strong skills in all factors except for physical skill and perception. Landscape architecture is similar to CEOs in requiring high leadership skills. However, unlike CEOs, it is less important for landscape architects to develop cooperation, education and initiative skills. This is intuitive. While CEOs must create a new vision while working with near equals, the leadership of landscape architects is more top down and within well-defined constraints. Police and detective work require similar skill sets, except police need to be more physical and detectives require more math, technical and education skills. Chemists and economists are another interesting pair of occupations to contrast. While both types of scientists require a good amount of initiative, a chemists rely on their mastery of equipment and technology while economists rely more on math.

Table 3 regresses the intensity of different occupational characteristics on the wage by occupation and industry. The specification is

$$Y_{j,i,t} = \sum_{F=1}^{8} \beta_F F_j + X_i + \epsilon_{j,i,t} \tag{1}$$

where j is occupation, i is industry, t is year, and X_i are industry fixed effects. All years of data, from 2006 to 2016, are included. In the first set of columns, $Y_{j,i,t}$ is the median wage in the occupation-industry. In the second pair, wage skewness is the outcome. It is measured as the average wage less the median wage, divided by the median wage, i.e.

$$Skew = (W_{Ave} - W_{Median})/W_{Median} \tag{2}$$

Table 3 shows that physical intensive occupations are significantly lower paid. To give a sense of the size of the effect, the occupation 'lawyer' has a physicality score of -1.52, and stonemasons have a physicality score of +2.53. Based on this factor alone, focusing on the specification without industry fixed effects, we would therefore expect the median lawyer to be paid \$16.93 more per hour than the median stonemason.

Cooperation intensive occupations are also significantly lower paid when not controlling for industry. The fact that the point estimate of this characteristic is significantly reduced when controlling for industry could be due to this form of employment being concentrated in the low paying retail industry.

Occupations intense in other factors are more highly compensated. Occupations which are more intensive in leadership, initiative, math and education are

	(1) Median Wage	(2) Median Wage	(3) Wage Skewness	(4) Wage Skewness
Physical	-4.181^{***}	-3.521^{***}	-0.003	-0.002
	(0.512)	(0.453)	(0.004)	(0.003)
Technology	0.604	-0.067	-0.019^{***}	-0.020^{***}
	(0.570)	(0.608)	(0.003)	(0.003)
Perception	0.914^{*}	0.486	-0.010^{*}	-0.006^{*}
	(0.371)	(0.340)	(0.004)	(0.003)
Leadership	3.967^{***}	4.063^{***}	0.006	0.007^{*}
	(0.630)	(0.657)	(0.004)	(0.003)
Cooperation	-1.649^{**}	-1.179^{*}	-0.001	0.005
	(0.543)	(0.592)	(0.004)	(0.003)
Initiative	4.685^{***}	4.449^{***}	0.020^{***}	0.018^{***}
	(0.503)	(0.447)	(0.005)	(0.004)
Math	1.802^{***}	1.671^{***}	0.005	0.000
	(0.405)	(0.437)	(0.004)	(0.003)
Educating	2.327^{***}	2.524^{***}	0.005	0.012^{***}
	(0.526)	(0.533)	(0.004)	(0.003)
Industry FE		X		X
Constant	21.508^{***}	20.874^{***}	0.076^{***}	0.078^{***}
	(0.650)	(0.573)	(0.004)	(0.004)
Observations	112,451	112,451	112,451	112,451

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Regression of occupation-industry median hourly wage (real 2006 dollars) and wage skewness on occupational skill intensity with and without industry fixed effects. All years pooled. Observations weighted by employment. Standard errors clustered at the occupation level. Standard errors in parentheses.

all significantly higher paid even after controlling for industry.

It is critical to remember that the coefficients estimated in table 3 *should not* be directly interpreted as returns to individual ability. It would be absurd to deduce that an individual who saw their physical skills increase should expect to see their wage decrease. Rather, the regression reports how the equilibrium wage of an occupation varies with the occupation's characteristics.

Many forces come to balance in the current equilibrium. To paraphrase Alfred Marshall, asking whether supply or demand sets a market equilibrium is like asking which blade of a scissor does the cutting. Occupations with the highest wage require skills that are hard to acquire. The relationship between occupational skill intensity and wages mostly corresponds to commonsense intuitions about particularly scarce and valuable skills. Physical, technical operation, and cooperation skills are seemingly abundant or easy to instill. A large percentage of US individuals in the US labor force have the physical strength and dexterity necessary to perform adequately in physical, menial occupations. The basic technical skills involved in troubleshooting, quality control, and installing and repairing equipment are relatively easy to instill. On the other hand, leadership, education, math, and grit seem scarcer and more challenging to impart.

Other factors may also contribute to the correlation between wage and occupational task intensity. These include things like the geographical dispersion of occupations. Some regions might have a higher concentration of a certain type of occupation but a lower cost of living as well. If occupations of specific tasks are particularly attractive (i.e. have a positive compensating differential) then workers may accept a wage penalty to accept jobs intensive that task. Future expectations may also play a role. As suggested by Edin et al. (2018) and others, people may sort into occupations based on whether they believe the occupation will be highly compensated in the future. If that is the case, then the wage associated with given skills may not only be a function of their current value, but their future value as well.

Table 3 also reports the skewness of the wage of occupations intensive in different factors. Skewness of an occupation-industry-year is defined as the average wage less the median wage divided by the median wage. Taking into account the constant term, almost all types of occupations are positively skewed. Occupations intensive in technical and perception skills are less skewed than average. Initiative intensive and, after controlling for industry, leadership and education intensive occupations are more positively skewed than the average. This is the consistent with papers that have found a large right tail for the most productive occupations, including leadership positions (see, for example, Brynjolfsson and Saint-Jacques (2015)).

These results are also consistent with intuitions about which types of occupations may have Pareto returns to excellence, and which have a long tail of mediocre workers with a cap on productivity. When working in a factory or driving a truck – occupations intensive in tech and perception respectively – productivity is limited by the technology being operated. It is hard to be two times as productive as the median worker in these tasks. On the other hand, those most skilled at education, initiative, and leadership tasks can be dramatically more productive than the median worker. The demand for top workers in these occupations more resemble the market for superstars described by Rosen (1981). Recall also that the highest paid occupations lack median and average wage data in some or all industries. Their wages are censored because they are so high. Chief executives are one example. If data were available for these occupations, the median and skewness of wages for high leadership intensity occupations would likely be even higher.

4 Identifying the Multiple Skills in SBTC

We are primarily interested in seeing what role these skills played in SBTC. We do so by measuring how wage and employment in occupations of different skill intensities has changed over time. We begin with the following specifications

$$W_{j,i,2016} - W_{j,i,2006} = \sum_{F=1}^{8} \beta_F F_j + X_i + \epsilon_{j,i,t} \tag{3}$$

and

$$ln(emp_{j,i,2016}) - ln(emp_{j,i,2006}) = \sum_{F=1}^{8} \beta_F F_j + X_i + \epsilon_{j,i,t} \tag{4}$$

Table 4 reports the results of these regressions. As can be seen, both wage and employment increased faster for leadership intensive occupations. Before industry controls, cooperation jobs saw faster employment growth and physical jobs slower wage growth. The specification with industry controls eliminates the significance of the latter results. This could be due to overcontrolling as cooperation and physically intense jobs are concentrated in a handful of industries.

The point estimates on these effects are moderately sized. An example of an occupation with a low leadership score is credit analyst with -2.08. An occupation with leadership intensity score of +1.93 is 'first line supervisors of police and detectives.' Our results indicate that police managers are predicted to have seen \$.899 dollars per hour in additional median hourly wage growth as a result of their greater leadership intensity and 16.4 percent faster employment growth.

Figure 1 plots the coefficients in table 4 for the specifications without industry fixed effects. As can be seen in the right panel, leadership and cooperation are the pair of characteristics with positive point estimates for both coefficients. This is consistent with an increase in demand for occupations intensive in these tasks. Such an increase in aggregate demand would tend to raise both employment and wages for these types of occupations. However, the wage increase for cooperative occupations is not significant, suggesting that an increase in supply for this occupation limited wage gains. For leadership intensive tasks, the inference that demand has gone up is particularly strong, as both point estimates are significant.

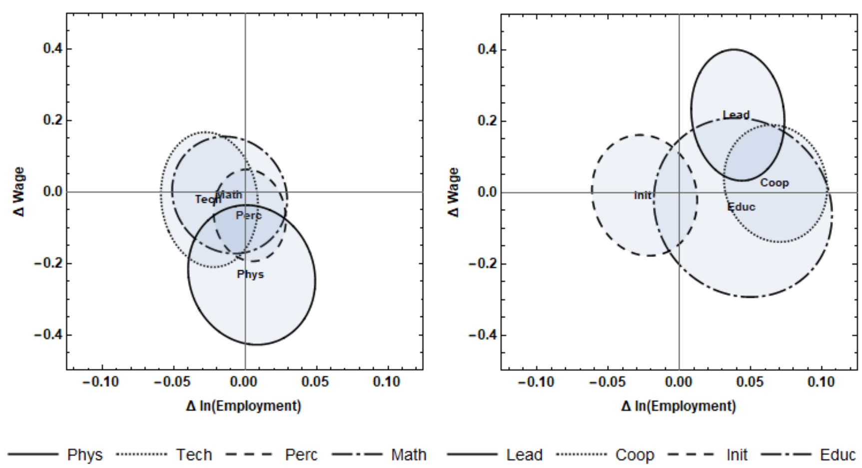

Figure 1: Scatterplot of the coefficients estimated in Table 4 with 95 percent confidence intervals. Tilt of the confidence ellipsoids due to correlation of the $\epsilon_{j,i,t}$ across models.

Point estimates associated with perception, physicality, and education intensive occupations, on the other hand, are positive for employment change and negative for wage change. This is consistent with an increased supply of workers in these types of occupations, with demand held relatively fixed. Perhaps these

	(1) ΔWage	(2) ΔWage	(3) Δln(Emp)	(4) Δln(Emp)
Physical	-0.232^{*}	-0.125	0.005	-0.009
	(0.100)	(0.093)	(0.023)	(0.024)
Technology	-0.022	-0.026	-0.025	0.012
	(0.096)	(0.104)	(0.017)	(0.019)
Perception	-0.066	-0.100	0.003	0.019
	(0.066)	(0.055)	(0.013)	(0.013)
Leadership	0.217^{*}	0.176^{*}	0.041^{*}	0.033^{*}
	(0.094)	(0.089)	(0.017)	(0.016)
Cooperation	0.025	-0.037	0.067^{***}	0.029
	(0.084)	(0.096)	(0.018)	(0.022)
Initiative	-0.008	0.010	-0.025	0.002
	(0.086)	(0.080)	(0.019)	(0.018)
Math	-0.009	0.066	-0.011	0.005
	(0.084)	(0.086)	(0.021)	(0.021)
Educating	-0.042	-0.092	0.044	0.034
	(0.128)	(0.125)	(0.032)	(0.028)
Industry FE		X		X
Constant	0.491^{***}	0.429^{***}	-0.025	0.008
	(0.107)	(0.101)	(0.019)	(0.018)
Observations	10,675	10,675	10,675	10,675

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Regression of change in median hourly wage and log employment by occupation-industry on 2006 occupational characteristics. Wage observations weighted by 2006 employment. Standard errors clustered by occupation.

are the types of occupations those whose jobs have been automated have found refuge in.

Figures 2 and 3 report how the wage premium and employment gains have evolved by occupational skill intensity over time. They plot estimates equivalent to those in equation 3 and 4 except that the difference estimated in between wages and log employment in 2006 and different annual end-points. For this reason, the plotted points and confidence intervals for year 2016 are the same as those reported in table 4 for the specification without industry fixed effects.

These figures reveal that the decrease in the wage for physical occupations snowballed smoothly over the entire interval, while the increase in wages for leadership intensive occupations occurred mostly in the first few years of the sample. The increase in cooperation intensive employment occurred entirely before 2010, while the increase in leadership intensive employment increased smoothly over the entire period, with a pause (mirroring the pause in wage growth) in the middle of the period.

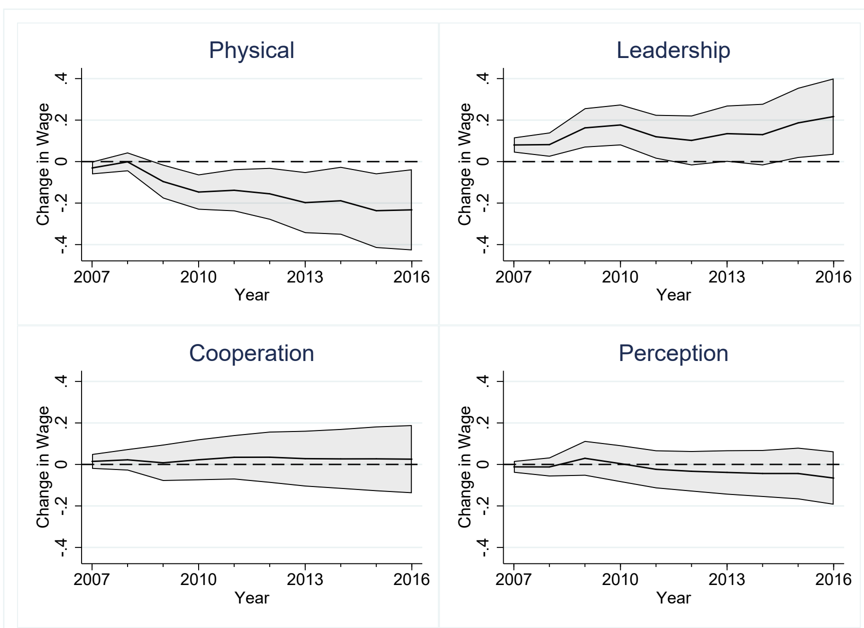

Figure 2: Plots of estimated coefficients from equation 3, with $W_{i,j,2016}$ replaced with the wage in an alternate year indicated on the x-axis. Observations weighted by 2006 employment. 95 percent confidence interval with SEs clustered by occupation displayed.

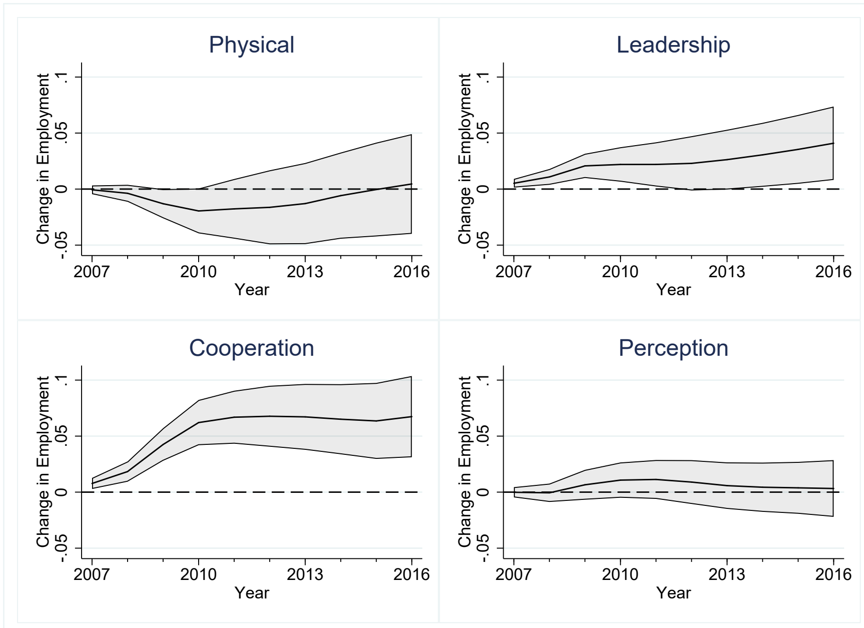

Figure 3: Plots of estimated coefficients from equation 4,with $ln(emp_{j,i,2016})$ replaced with log employment in an alternate year indicated on the x-axis. 95 percent confidence interval with SEs clustered by occupation displayed.

Table 5 reports how employment changed for occupations of different skill intensities in aggregate. Occupations are binned by quartile, using 2006 employment levels, and then the change in employment controlling for average employment growth was calculated. Occupations in the top quarter of physicality lost about 1.5 million excess net-jobs. Occupations in the bottom quartile of leadership and cooperation added .5 million and 2.3 million fewer net-jobs respectively than unbiased employment growth would have predicted. Top quartile occupations in these characteristics added over 2.2 and 1.1 million excess net jobs. Also interesting is the fact that while employment growth was not significantly biased towards or against math, tech, or perception skills, the variance of skill intensity moved for these occupations in different ways. Most employment growth was in occupations requiring moderate amounts of math and tech. Meanwhile, employment growth was polarizing along the dimension of perception intensity, with disproportionate job growth in the most and least perception intense occupations.

Overall, these changes are consistent with technological change reducing de-

Excess Employment Growth by Skill Intensity

	Top Quartile	Middle Half	Bottom Quartile
Physical	$-1,533,103$	$1,809,815$	$-276,713$
Technology	$-889,513$	$1,044,035$	$-154,523$
Perception	$350,488$	$-1,060,985$	$710,498$
Leadership	$2,244,428$	$-1,694,515$	$-549,913$
Cooperation	$1,158,518$	$1,226,225$	$-2,384,743$
Initiative	$-952,733$	$110,315$	$842,418$
Math	$-807,213$	$972,215$	$-165,003$
Educating	$594,968$	$83,555$	$-678,523$

Table 5: Change in occupational employment by factor intensity percentile above unbiased employment growth, rounded to the nearest integer. Occupations binned into percentiles weighted by 2006 employment. 4,988,450 additional net-jobs were added from 2016 versus 2006, so total employment growth in occupations in the top or bottom quartile of any skill factor can be determined by adding 1,247,112 to the number in the table. Because excess job growth is reported, the sum of excess net-job growth within each row adds to zero. Data is restricted to the occupations and industries used in the main regressions (e.g. table 4).

mand for physical intensive jobs, with some workers moving up the skill chain into leadership intensive occupations, and others sorting into cooperation intensive jobs with less wage growth. That being said, it is important to remember that we cannot rule out alternative interpretations of these coefficients. In particular, sorting of individuals with different productivities into occupations might break the above interpretations. For example, suppose – holding demand for tasks fixed – those with very high latent general productivity began enjoying leadership positions relatively more. The impact on the average wage in high leadership occupations would be the combination of a downward force – a downward sloping demand curve for leadership tasks – and an upward force – the higher average productivity of those who wish to sort into leadership tasks. Similarly, employment change in these occupations would tend to increase because of the increased attractiveness of the job but decrease due to the increased productivity of those switching to that form of employment.

4.1 The Changing Importance of Skills and IT

Therefore, we now turn our attention to how changes in the wages and employment occupational skill characteristics is mediated by technology. The following tables rerun the specification in equation (1) with the modification that occupations or industry be in the bottom/top 40 percentiles of some characteristic.[4]

	(1) ΔWage	(2) ΔWage	(3) Δln(Emp)	(4) Δln(Emp)
Physical	−0.008	−0.239	−0.056**	−0.009
	(0.144)	(0.140)	(0.019)	(0.029)
Technology	0.160	−0.259	0.002	−0.002
	(0.133)	(0.181)	(0.017)	(0.041)
Perception	−0.136	−0.162	0.052*	0.070
	(0.130)	(0.141)	(0.021)	(0.042)
Leadership	0.367*	0.219	−0.001	0.055*
	(0.154)	(0.151)	(0.032)	(0.025)
Cooperation	0.138	−0.103	0.121***	0.035
	(0.117)	(0.148)	(0.024)	(0.034)
Initiative	−0.027	0.022	−0.050*	0.009
	(0.120)	(0.117)	(0.025)	(0.026)
Math	−0.057	−0.034	−0.022	0.034
	(0.093)	(0.142)	(0.016)	(0.040)
Educating	0.185	−0.160	0.008	0.041
	(0.130)	(0.165)	(0.039)	(0.039)
Constant	0.411*	0.578***	0.051*	−0.074*
	(0.171)	(0.151)	(0.020)	(0.036)
Repetitiveness Split	Low	High	Low	High
Observations	4,057	4,561	4,057	4,561

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Regression of change in median hourly wage and log employment by occupation-industry on 2006 occupational characteristics. Wage observations weighted by 2006 employment. Standard errors clustered by occupation. Sample split by occupation repetitiveness, as defined by O*NET element, in 2006. Bottom and top 40 percentile occupation bins with equal total employment in 2006.

Table 6 divides our regression on occupations by the repetitiveness of the occupation as measured by an O*NET question. For technology intensive occu-

[4]Weighing by occupational employment, using 2006 occupational employment.

pations wage growth is stronger when the occupation is routine. For initiative and leadership intensive occupations this pattern is reversed, with stronger wage gains when the occupation is non-repetitive.[5]

Table 7 divides occupations by their computer usage intensity. Computer intensive occupations which are high in leadership and initiative tended to see faster wage growth, while occupations high in cooperation saw faster wage growth when the occupation involves less computer use. This makes sense: leadership and initiative are complemented by information technologies that allow workers to spread their novel ideas. On the other hand the basic skills involved in cooperation are more likely to be automated by deepening IT capital. Most dramatically, physically intensive computer using occupations saw large wage decreases, while those which are not computer intensive saw increases. This is consistent with automation due to robotics.

Table divides industries by IT capital intensity in 2016. This is defined as the current cost of IT forms of capital as a ratio of total nonresidential fixed private investment in the industry. IT capital includes computer or server hardware and software.[6] More computer intensive industries saw smaller cooperation wage and employment growth.

The main lesson to draw from tables 7 and 8 is how technology differently interacts with leadership and cooperation. The overall increase in wages for leadership intensive occupations is concentrated in occupations and industries with high computer use or ITC investment. On the other hand, the overall increase in employment for cooperation intensive occupations is driven by low computer use occupations and low ITC intensity industries. This is consistent with our hypothesis that technological change is boosting the abilities and wages of managers especially in high-tech industries, while individuals who only have cooperation skills are finding refuge in low-tech industries and occupations.

[5] Appendix table 14 divides occupations into high and low unstructuredness, and yields similar results. Structured occupations high in initiative and education saw relative wage declines, while those high in technology use saw larger increases.

[6] Forty-four three digit industries are able to be matched exactly to the rest of the data. The remaining industries were matched many-to-one (the BEA data is coarser) with 2006 employment weighted averages.

	(1)	(2)	(3)	(4)
	ΔWage	ΔWage	Δln(Emp)	Δln(Emp)
Physical	0.322*	−0.380*	−0.027	−0.004
	(0.136)	(0.158)	(0.042)	(0.037)
Technology	0.116	−0.195	−0.055*	0.029
	(0.068)	(0.149)	(0.026)	(0.025)
Perception	−0.044	−0.129	0.007	0.033
	(0.039)	(0.110)	(0.019)	(0.024)
Leadership	0.145	0.373**	0.009	0.050*
	(0.078)	(0.134)	(0.045)	(0.021)
Cooperation	0.140*	−0.047	0.098***	0.050
	(0.060)	(0.127)	(0.028)	(0.031)
Initiative	−0.252**	0.310	−0.050	−0.012
	(0.082)	(0.185)	(0.033)	(0.039)
Math	−0.229***	0.135	−0.029	0.010
	(0.043)	(0.120)	(0.020)	(0.034)
Educating	0.009	−0.151	−0.017	0.065
	(0.088)	(0.182)	(0.048)	(0.045)
Constant	−0.091	0.525***	−0.036	−0.024
	(0.181)	(0.111)	(0.046)	(0.022)
Computer Use Split	Low	High	Low	High
Observations	2,877	6,062	2,877	6,062

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Regression of change in median hourly wage and log employment by occupation-industry on 2006 occupational characteristics. Wage observations weighted by 2006 employment. Standard errors clustered by occupation. Sample split by occupation computer use, as defined by O*NET element, in 2006. Bottom and top 40 percentile occupation bins with equal total employment in 2006.

5 Unpacking Social Skills

Our analysis revealed that leadership is increasingly important. This is in line with the finding of Deming (2017) that social skills are increasingly important. According to his index of social skill intensity, the share of employment in occu-

	(1)	(2)	(3)	(4)
	ΔWage	ΔWage	Δln(Emp)	Δln(Emp)
Physical	−0.193	−0.241*	0.034	−0.013
	(0.106)	(0.121)	(0.029)	(0.022)
Technology	−0.064	−0.000	−0.018	−0.013
	(0.089)	(0.158)	(0.028)	(0.023)
Perception	−0.126*	−0.027	0.008	0.014
	(0.059)	(0.091)	(0.017)	(0.018)
Leadership	0.212*	0.220	0.048*	0.041*
	(0.098)	(0.126)	(0.021)	(0.018)
Cooperation	0.050	−0.017	0.082***	0.028
	(0.074)	(0.132)	(0.023)	(0.026)
Initiative	0.096	−0.030	−0.054*	0.005
	(0.094)	(0.121)	(0.023)	(0.021)
Math	0.035	−0.023	0.005	0.014
	(0.056)	(0.103)	(0.022)	(0.022)
Educating	0.145	−0.150	−0.009	0.030
	(0.124)	(0.176)	(0.034)	(0.033)
Constant	0.707***	0.413**	−0.052	−0.047*
	(0.136)	(0.137)	(0.028)	(0.021)
ITC Intensity Split	Low	High	Low	High
Observations	4,080	4,923	4,080	4,923

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Regression of change in median hourly wage and log employment by occupation-industry on 2006 occupational characteristics. Wage observations weighted by 2006 employment. Standard errors clustered by occupation. Sample split by industry ITC intensity in 2016 allowing one-to-many and many-to-one industry matches between BEA and BLS data. Bottom and top 40 percentile occupation bins with equal total employment in 2006.

pations requiring high levels of social interaction grew by nearly 12 percentage points. What is interesting is that our index found at least two *different types* of social skills: Leadership, which is more closely associated with wage increases, and cooperation, which is more closely associated with employment increases. In this section we compare our results on leadership and cooperation to those of Deming (2017) on social skills. Following Deming (2017) social skill intensity of an occupation is measured as the average of four O*NET level measures: social perception, coordination, persuasion and negotiation. This measure is then rescaled to an index lying between one and ten.[7]

Figure 4 contrasts our measures of social skill with those of Deming (2017). The first panel plots cooperation and leadership intensity scores by occupation. As expected, the two occupational characteristics are uncorrelated. By construction these factors are orthogonal. The latter pair of panels compares our measures of social skills with Deming's social skill index (hereafter: socialness). It is significantly positively correlated with both. Notably, this is despite the fact that none of the O*NET elements used in the construction of socialness are used in the final calculation of our factors. The adjusted r^2s in a regression of the socialness on leadership and cooperation are .172 and .047 respectively. So, of the two orthogonal factors, socialness is more closely related to leadership.

It is clear that our measures of occupational social skill instensity are correlated with Deming's, but still differ significantly from it. To further provide a sense of how these three measures are distinguished, table 9 reports high and low leadership and cooperation occupations for occupations with a high socialness score and a low socialness score. Psychiatrists and clergy are both evaluated as high social skill occupations. However, our factors distinguish between the first, which is considered high cooperation and low leadership, while the latter is evaluated as high leadership but requiring only moderate cooperation.

High Deming Social Skill Index Occupations

	High Leadership	**Med/Low Leadership**
High Cooperation	Education Administrator	Psychiatrist
Med/Low Cooperation	Clergy	Sales Engineers

Low Deming Social Skill Index Occupations

	High/Med Leadership	**Low Leadership**
High/Med Cooperation	Hazmat Worker	Sports Bookies
Low Cooperation	Motorcycle Mechanic	Sewing Machine Operator

Table 9: Occupations with high and low cooperation and leadership scores for occupations with high and low Deming Social Skill index measures.

We next wish to juxtapose the importance of our social skill measures to

[7]Unlike Deming, we use December 2006 O*NET scores and 2006 occupational employment rather than 1997 data as he does. We thank Deming for making his code easily available on his website.

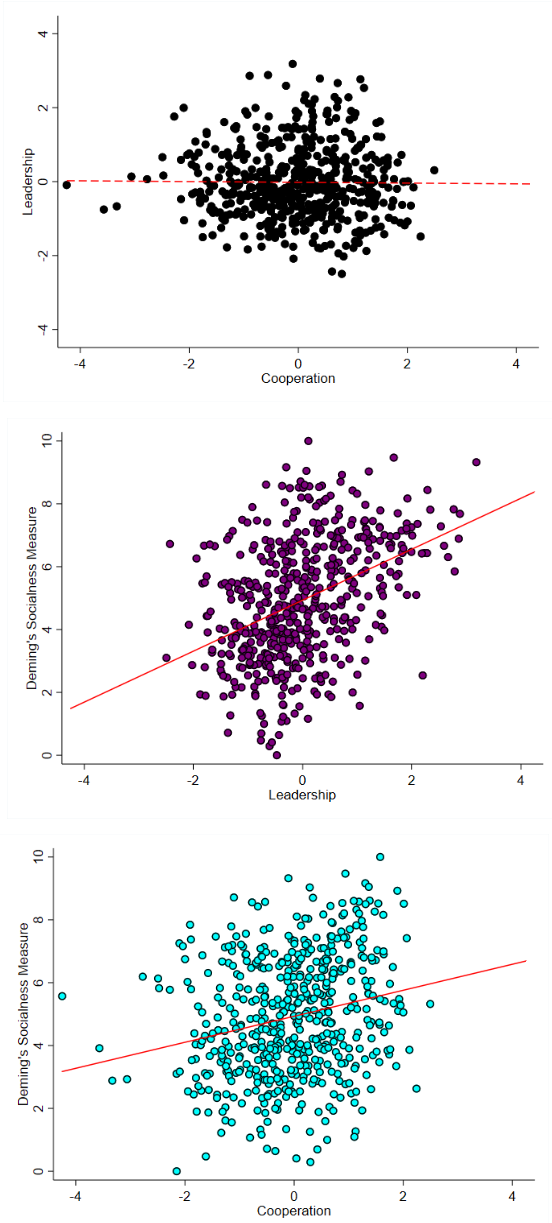

Figure 4: Scatterplots of occupational task intensity and lines of best fit relating Deming's social index and our two primary social skill measures. Socialness is positively associated with both leadership and cooperation skills, which are themselves orthogonal by construction. The adjusted r^2s in a regression of the socialness on leadership and cooperation are .172 and .047 respectively.

SBTC with Deming's. Table 10 does so by re-running specification (1) with the addition of socialness as an additional regressor.

	(1)	(2)	(3)	(4)
	ΔWage	ΔWage	Δln(Emp)	Δln(Emp)
Physical	-0.286^{*}	-0.191	0.033	0.016
	(0.136)	(0.127)	(0.033)	(0.034)
Technology	-0.026	-0.029	-0.022	0.013
	(0.097)	(0.103)	(0.018)	(0.020)
Perception	-0.048	-0.079	-0.006	0.012
	(0.067)	(0.055)	(0.013)	(0.014)
Leadership	0.268^{*}	0.244^{*}	0.013	0.008
	(0.124)	(0.120)	(0.028)	(0.028)
Cooperation	0.044	-0.014	0.057^{**}	0.020
	(0.098)	(0.109)	(0.021)	(0.025)
Initiative	0.052	0.089	-0.057	-0.027
	(0.125)	(0.107)	(0.031)	(0.031)
Math	-0.003	0.075	-0.014	0.001
	(0.081)	(0.081)	(0.019)	(0.020)
Educating	0.038	0.014	0.001	-0.006
	(0.117)	(0.108)	(0.018)	(0.018)
Deming's Socialness	-0.066	-0.087	0.036	0.033
	(0.095)	(0.088)	(0.021)	(0.020)
Constant	0.840	0.890	-0.214	-0.165
	(0.504)	(0.458)	(0.115)	(0.114)
Industry FE		X		X
Observations	10,675	10,675	10,675	10,675

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Regression of change in median hourly wage and log employment by occupation-industry on 2006 occupational characteristics and Deming Social Skill intensity. Wage observations weighted by 2006 employment. Standard errors clustered by occupation.

In explaining the change in occupational wage, socialness enters negatively, though the point estimate is not significant. The point estimate of the effect of leadership remains positive and significant. Both these observations are true for the specification with and without industry fixed effects. The point estimates on the effect of leadership on wage growth are actually somewhat increased from the baseline specification. In these specifications the dimension of sociability that Deming captures is actually a negative predictor of wage growth once leadership is controled for. The significant negative point estimate on the physicallity of an occupation, when industry FEs are not included, is also similar to the specification without socialness.

Including socialness in the explanation of employment change, in the specification without industry FEs, leaves the point estimate of the effect of co-operation unchanged. However, it reduces the point estimate of the effect of leadership. Socialness itself enters positively in the prediction of employment growth, but not significantly so, whether or not industry FEs are included.

The results in table 10 are consistent with cooperation intensity being most useful for predicting occupational employment growth, leadership and physicallity being most predictive for wage growth, and socialness not being particularly important for either, once the above are controlled for. However, one potential concern with this interpretation is that it is over-fitting. Ten thousand observations is a healthy amount, but even with only nine regressors there is the potential that occupational characteristics with a noisier relationship to the data are obscuring robust relationships between some factors and employment and occupation growth. To deal with this possibility, the final section of our paper proceeds to LASSO estimation. This is a machine learning technique designed to avoid overfitting predictions with many regressors. When there are several colinear (or nearly so) regressors, or alternatively, many noisy ones, it is good at throwing out all but the most predictive regressors.

Table 11 reports the results of a LASSO regression on our eight endogenously determined variables and three indexes constructed following Deming (2017). These are socialness, as well as measures of occupational routineness and non-routine-math intensity. λ, a parameter which governs how coefficient estimates are penalized, is selected using K-fold cross validation to minimize mean-squared error.[8]

Selecting λ to minimize cross-validation mean squared error, all regressors

[8] This means that the exact λ, and therefore the variables which are retained, in LASSO regression is dependent on the seed used. However, the presented results are by far the most common. Tables with exogenous λ selections are deterministic.

	(1)	(2)
	ΔWage	Δln(Emp)
Physical	−0.129	−0.008
Technology	−0.044	−0.030
Perception	−0.107	0.014
Leadership	0.210	0.028
Cooperation	−0.035	0.054
Initiative	0.061	−0.006
Math	−0.105	−0.132
Educating	−0.069	0.049
Deming's Routineness	0.042	−0.026
Deming's Socialness	0.064	0.011
Deming's Math	0.194	0.094
Constant	−0.526	−0.308
Observations	10,675	10,675
λ	0.000	0.000
r^2	0.031	0.046

Table 11: LASSO regression of occupation skill intensity and three Deming measures on occupational wage and employment change. LASSO implemented in STATA using the 'elasticregress' package. Lambda selected using K-fold cross-validation.

are retained. λ takes on it's minimum possible value. The most important regressors, phsycial, leadership, and cooperation, retain their previous signs and approximate magnitudes. However, the estimate of the effect of socialness on wage growth flips to positive.

Deming (2017) also identifies increasing complementarity between social and mathematical skills. He finds that wages in occupations requiring both strong mathematical and social skills grew by about 25 percentage points from 1980 to 2012. But are there other important complementarities between skill sets which have emerged due to technological change? In the last regressions of this paper, we use LASSO to examine the role of our 8 endogenously derived factors, Deming's 3 occupational characteristic indexes, and all of their interactions on occupational wage and employment change.

Table 5 reports the estimates of a LASSO regression of change in occupational wage on occupational characteristics. There are 10 non-interacted and 45 (10 choose 2) interacted regressors in all, for a total of 55. In the table, only regressors with non-zero coefficient estimates with some λ are reported.

In a series of four regressions we increase λ exogenously and see which re-

	(1) ΔWage	(2) ΔWage	(3) ΔWage	(4) ΔWage
Physical	-0.183	-0.118	-0.025	0
Leadership	0.169	0.100	0.044	0
Deming Socialness	0.045	0	0	0
Deming Math	0.055	0	0	0
Physical*Leadership	-0.008	0	0	0
Physical*Math	-0.102	-0.044	0	0
Perception*Leadership	-0.045	-0.016	0	0
Perception*Cooperation	-0.076	-0.031	0	0
Leadership*Education	-0.099	-0.081	0	0
Initiative*Deming Math	0.016	0	0	0
Deming Social*Deming Math	0	0.019	0.019	0.014
Constant	0.361	0.405	0.420	0.527
Observations	10675	10675	10675	10675
λ	0.075	0.100	0.200	0.300
r^2	0.034	0.031	0.023	0.016

Table 12: LASSO regression of occupation skill intensity and three Deming measures, as well as their forty-five interactions, on occupational wage change. Only regressors that take on non-zero values for some reported λ are presented. LASSO implemented in STATA using the 'elasticregress' package. λ selected exogenously.

gressors are retained. The regressors which are the last to be discarded are the most important individually in explaining wage or employment growth. With λ at a moderate level, .075, ten regressors are retained. Four of these are raw factors which retain the signs estimated before. For example, leadership and socialness enter positively, while physical enters negatively. The next six terms are interactions. Occupations which are leadership intensive saw wage increases in general, but jobs that are intensive in both this and physicality, perception, or education saw smaller increases or even decreases. Leadership positions that also require physical exertion or perception are likely to be lower level positions, so this result is consistent with that of the previous table. Also entering negatively are the interaction of perception and cooperation and the interaction of physical and math. The interaction of initiative and Deming's non-routine-analytical math measure enters positively.

Increasing λ to the high value of .2, the only regressors retained are physical, leadership and the interaction of Demings' socialness and non-routine-analytical math measures. The fact that this last measure only takes on a non-zero coefficient for high values of λ suggests that this interaction term is a good summary

	(1)	(2)	(3)	(4)
	Δln(Emp)	Δln(Emp)	Δln(Emp)	Δln(Emp)
Leadership	0.008	0.004	0	0
Deming Routineness	-0.004	-0.002	0	0
Deming Socialness	0.042	0.038	0.035	0.020
Physical*Leadership	-0.033	-0.026	-0.018	0
Physical*Education	-0.010	0	0	0
Tech*Education	-0.004	0	0	0
Perception*Deming Social	0.005	0.003	0.001	0
Cooperation*Math	-0.005	0	0	0
Math*Deming Social	-0.001	0	0	0
Constant	-0.198	-0.197	-0.187	-0.115
Observations	10675	10675	10675	10675
λ	0.030	0.040	0.050	0.080
r^2	0.040	0.033	0.027	0.015

Table 13: LASSO regression of occupation skill intensity and three Deming measures, as well as their forty-five interactions, on occupational employment change. Only regressors that take on non-zero values for some reported λ are presented. LASSO implemented in STATA using the 'elasticregress' package. λ selected exogenously.

variable for the independent effects of Demings' socialness and math, which take on a coefficient of zero. Increasing the value of λ one more time, only this last interaction term remains. A main takeaway from table 5 is that, including all 45 interactions, physical, leadership and the interaction of Demings' socialness and math are the most important predictors of occupational wage growth.

Table 13 repeats the same exercise with change in log employment as the outcome of interest. For a high value of λ, .08, the only retained term is socialness, marking it as the most important predictor of employment growth. For lower levels of λ, the nine regressors retained include leadership, which enters positively, and cooperation interacted with math, which enters negatively. This last interaction is surprising, given that cooperation enters positively as a predictor of occupational employment growth in our OLS specifications. However, it is intuitive that jobs requiring both cooperation and the basic numeracy that our math factor measures have decreased in employment due to technological shifts.

6 Conclusion

Previous research has established SBTC as an important force in the evolution the labor market. Better understanding how governments and individuals can re-skill themselves to deal with these challenges is therefore of utmost importance. However, a limitation of this research has been its reliance on poorly motivated and ad-hoc measures of skill. In this paper we used a unsupervised machine learning technique to organize US occupations by their skill requirements, and then analyzed how occupations of various characteristics were impacted by SBTC.

This technique endogenously identifies eight factors as jointly characterizing occupational skills. These factors have intuitive relationships to the wage distribution. We find that occupational leadership, physical, and cooperation intensity are the most significant predictors of occupational wage and employment growth. Our technique does not entirely eliminate human judgment in the construction of occupational measures because it relies on the questions that O*NET decides to asks, and the qualitative judgments they make. But it almost certainly has less of a problem than the arbitrarily constructed indexes that are common in this literature.

Leadership positively predicts employment and wage growth, suggesting an increase in demand. Cooperative jobs primarily experienced increases in employment, consistent with an increase in the supply of individuals seeking these jobs. Physically intense jobs saw decreases in wage, consistent with an decrease in demand for these types of jobs due to robotic automation. Splitting industries and occupations by ITC use, we find further support for these hypotheses: the decrease in wages for physical jobs and increase in wages for leadership jobs are driven by high-tech occupations and industries, while the increase in cooperation intensive jobs is concentrated in low tech occupations and industries.

We identify two measures of social skills that are important to SBTC. Therefore we juxtapose our results with Deming (2017), a paper on SBTC utilizing indexes. We show that his finding, an increased role for the importance of social skills, is underpinned by two distinct trends – the increase in wages for leadership occupations, and an increase in employment for cooperative occupations. This is further confirmed by looking into the underlying elements used to construct leadership, cooperation and socialness as management oriented elements are more closely associated with wage growth, and empathetic oriented elements are more closely associated with employment growth. Deming's socialness is a useful summary of these distinct trends, but is an example of how arbitrary indexes can overlook important underlying variation.

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A Additional Tables

	(1) ΔWage	(2) ΔWage	(3) Δln(Emp)	(4) Δln(Emp)
Physical	0.215	−0.234	−0.026	0.000
	(0.113)	(0.177)	(0.036)	(0.029)
Technology	0.221**	−0.059	−0.021	−0.014
	(0.077)	(0.176)	(0.026)	(0.033)
Perception	0.031	−0.210	0.010	0.027
	(0.058)	(0.188)	(0.015)	(0.031)
Leadership	0.121	0.207	0.070*	0.028
	(0.151)	(0.137)	(0.028)	(0.026)
Cooperation	0.163	0.086	0.052*	0.036
	(0.092)	(0.165)	(0.020)	(0.035)
Initiative	−0.327***	−0.045	0.006	−0.027
	(0.088)	(0.183)	(0.027)	(0.045)
Math	−0.137	0.075	0.006	−0.020
	(0.078)	(0.153)	(0.019)	(0.040)
Educating	−0.213*	−0.077	−0.031	0.089*
	(0.085)	(0.186)	(0.040)	(0.045)
Constant	−0.004	0.484***	−0.005	0.016
	(0.160)	(0.125)	(0.044)	(0.034)
Unstructuredness Split	Low	High	Low	High
Observations	2,872	5,843	2,872	5,843

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Regression of change in median hourly wage and log employment by occupation-industry on 2006 occupational characteristics. Wage observations weighted by 2006 employment. Standard errors clustered by occupation. Sample split by occupation unstructuredness, as defined by O*NET element, in 2006. Bottom and top 40 percentile occupation bins with equal total employment in 2006.