Identifying the Multiple Skills in Skill-Biased Technical Change

Completed Research Paper

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Abstract

US median wages have stagnated for 30 years, yet this masks a surprising amount of variation among different groups. A large literature documents that skill-biased technical change (SBTC) has led to substantial real wage increases on average for those with at least a college degree, and declines on average for those with less education. However, SBTC is not a single dimensional construct. We identify seven orthogonal dimensions of skill across 514 occupations and examine how the earning power of each skill changed over the period 2006-2014. We find that (1) different skills accrue different levels of wage, (2) these wage effects vary on both the actual use of IT in the occupation as well as the general level of IT intensity in the industry, and (3) the technology-skill effects on wage are nonlinear. We discuss implications for workers, educators and policymakers.

Keywords:
Skill-biased technical change, Empirical analysis, Economic impacts, Income inequality, Skills

Introduction

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

– Henry David Thoreau

Median wages have been largely stagnant in the United States for 30 years (Cowen, 2011). Yet this headline masks a surprising amount of variation in wages among different groups of workers. For example, Acemoglu & Autor (2010), hereafter AA, showed that workers with at least a college education have experienced substantial real wage increases over the past four decades. Meanwhile the majority of workers – those with less than a college degree – actually suffered wage declines during those years.

Another important, and related, trend is the effect of rapid technological advance on productivity and employment. Historically, productivity and employment have grown in tandem. As productivity grew, it led to more jobs for workers. But something happened in the early 2000s, about the time that computers moved from internal corporate automation to information and collaboration activities that spanned geographies and corporate boundaries. Productivity growth in the 2000s and beyond has not been matched by a concomitant increase in employment or wages (Brynjolfsson & McAfee, 2014). In part, this reflects the substitution of computers for people, especially in the middle of the skill distribution, resulting in higher competition – and lower wages -- for jobs at the middle and lower end of the skill distribution (AA). As the capabilities of automation increase, the substitution challenges may also increase, with negative wage implications for more and more workers.

While employment and wages are declining in many occupations, they are increasing in others. For instance, there are fewer bank tellers in the United States in 2014 than in 2006, and those that remain make less money, but the demand for, and wages of, physician assistants have increased significantly.

Beyond changes in skill demand on the *extensive* margin (ALM) for occupations containing certain skills, technology is also changing skill demand on the *intensive* margin by modifying the skill content of the occupations themselves. For example, there are fewer secretaries than in 2006, but the remaining ones do more cognitive and interpersonal work than before, and they earn higher wages.

What is behind the variance in employment and wage growth across occupations in the past decade? In this study, we set out to understand the role of technological advances. Building on the methods developed by MacCrory *et al.* (2014), hereafter MWAB, we identify seven dimensions of skill across 514 jobs in 2006, and then extend the analysis using US labor market data. We examine how wages and employment for each skill dimension have changed over the period 2006-2014. We then add IT investment and capability data to estimate how technological change can explain those changes.

We find evidence that skill-biased technical change (SBTC) affects skills in distinct ways. Occupational use of IT exhibits stronger biases than industry IT intensity. Wage changes in the presence of IT suggest that some skills are complements for technology while others are either substitutes or do not interact. Furthermore, the effects are non-linear; quantile analysis of IT use exhibits clear peaks and other non-linear effects upon wages, suggesting that testing means or simple interactions will miss the some of the changes in SBTC. Finally we find that above-average wages are flowing to occupations that require high skills in two or more dimensions simultaneously; this is not the time to be a relatively unskilled worker. Our findings have important implications for the analysis of SBTC and policies to address it.

Background

Technical change has been an important driver of productivity and wages for centuries. From 1811-1816, the Luddites in England protested the effects of labor-saving technologies on artisan skills and jobs in the textile industry. More recently, technology-mediated changes such as seaport automation (Bonney, 2012; Strunsky, 2012), trade globalization (Tizon, 1999; WTO History Project, n.d.), and increasing wage inequality (Gumbel, 2014; Wingfield, 2014) have been met with strong opposition from workers. In each case, workers protested changes that they asserted could result in fewer jobs or lower standards of living. While technology cannot explain the full extent of changes in wages – globalization, offshoring, and other macroeconomic trends are also factors – it is certainly a contributor to those changes.

Economists studying SBTC have gathered substantial evidence that the effects of technology on work and employment – particularly IT that substitutes for routine work – are profound (AA, ALM). Economic cycles can exacerbate these effects; SBTC such as automation can “lead to job polarization that is concentrated in downturns and recoveries … that are jobless” (Jaimovich & Sui, 2014).

SBTC is not without its detractors. Card and DiNardo (2002) show that several inequality measures related to work and employment respond to factors other than technology, which they note is often proxied by the passage of time. The dependent variables typically used are designed to measure the impact of “unobserved skills,” namely any skills not captured by education and age. We chose our data sources specifically to observe as large a set of skills as possible, some of which are correlated with education (*e.g.*, Technology Design) and some of which are not (*e.g.*, Stress Tolerance). We also chose direct measures of IT use at the occupation and industry levels rather than proxy technology by the passage of time. We believe these data allow us better to determine the extent to which SBTC is responsible for reduced wages for routine tasks.

Routine tasks are not the only ones at risk, however. A computer’s core competency is not in performing *routine* tasks per se; it is in performing tasks that can be *codified* regardless of how often they are performed (Levy and Murnane 2004). While many routine tasks represent low-hanging fruit for codification, non-routine risks are not immune. Computers have begun to perform non-routine tasks such as writing newspaper stories (Fassler, 2012; Colford, 2014), developing new recipes (Jackson, 2014), and driving cars (Kessler, 2015).

Technology-labor substitution is not the only way in which technology affects labor demand. Beyond extensive changes in demand for jobs, SBTC is also creating intensive change to the content of the jobs themselves (ALM) by substituting, complementing and transferring skills within the occupation (Cerrato, 2011; Matthew, 2013; Elliot *et al.*, 2014). These technologies can reduce demand for specialists by shifting their tasks to non-specialist workers in other occupations.

Understanding SBTC requires the systematic characterization of skills across occupations. Earlier, we cited evidence for a "college premium" in wages. College, however, is not a skill. It is meant to provide a set of skills that apparently are valued in the labor market. To examine skills and wages more systematically requires a clear and measurable typology of skills. A common practice in prior literature has been to proxy a single dimension of "skill" by education level or wages in a reference year. More recent work has recognized several dimensions or mutually exclusive categories of skill. For example:

- A 2×2 set of skills along Cognitive/Manual and Routine/Non-routine axes (ALM) and refinements of this system (AA; Autor & Dorn, 2013)
- Manipulation, creative intelligence and social intelligence (Frey & Osbourne, 2013)
- Language, reasoning, vision and movement (Elliot, 2014)
- Five core competencies of humans: large muscles, small muscles, keeping processes on track, social reciprocity, and thinking up new things (DeLong, 2014)

Most of these efforts represent progressively more precise a-priori classifications of skills for specific contexts. Every one of the above schema has shown that the impact of SBTC has been different at different points of time. Recently, MWAB offered a more nuanced approach to taxonomy construction by empirically deriving skill dimensions through principal component factor analysis of detailed data on occupation skill requirements.

AA demonstrate that a skill premium is not simply the result of one group's wages growing faster than another's. SBTC can actively harm the earning power of some groups. Consider a person entering the workforce who needs to choose a skill in which to specialize. The canonical SBTC model states that this person's wages might grow more slowly with the "wrong" skill, but technical progress still lifts all wages to a greater or lesser degree. AA show that this is emphatically not the case. Whether using a simple proxy for a single skill (e.g., education or wage percentile) or a richer taxonomy of skills, multiple SBTC studies show declines in real wages of some groups for reasons that can plausibly be attributed to technical change. Our goal is to identify empirically the skills and biases that explain the variation in SBTC across different occupations using a model that is rich enough to guide educators, policymakers, and people entering the workforce.

Data and Methods

AA used US Census Bureau data to construct a roughly decadal panel of wages and employment to detect long-term trends in skill-biased technical change. Census data were not collected for this purpose, yet compared to other potential sources Census data have the advantage of fairly consistent constructs for long periods. We seek to identify patterns on much shorter time-scales and thus have the ability to use administrative data collected expressly to measure employment, wages and skills.

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 for which 2014 are the latest available. For each occupation, OES reports the number of people in that occupation plus several statistics about the salary distribution including the mean and the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles. We follow prior literature (AA, especially their Figures 7 and 8) in using the 10^{th}, 50^{th} and 90^{th} percentiles to describe the wage distribution. All wages are deflated to constant 2006 dollars using the annual Consumer Price Index for all urban households (CPI-U) published at www.bls.gov/cpi. We construct a comparable sample using the Census Bureau data for robustness, with a replication of Table 3 in the Appendix.

We draw our skill data from the Department of Labor's O*NET dataset (available at www.onetcenter.org). We use the latest version published in a year to represent that year. For each occupation, O*NET reports hundreds of characteristics that include required abilities, important skills, working conditions, and typical tasks. Consistent with AA and MWAB, we use the importance rating rather than the level rating when both exist for a characteristic.

Following MWAB, we performed principal component factor analysis on the O*NET characteristics in a reference year. A set of "Work Style" variables was added to O*NET in 2003, with ratings populated as occupations were updated. The Standard Occupation Code system was updated in 2006, by which time virtually all occupations in O*NET had "Work Style" ratings. We therefore chose 2006 as our reference year for all occupation characteristics and identified differences in wages and employment that occurred across the sample period of 2006 to 2014.

We begin with all importance items in O*NET except for 4.A.3.b.1 "Interacting with Computers" because we will later use that rating for sample splits. We retained those items that loaded on any factor with an absolute value of 0.7 or higher after varimax rotation, and retained each factor with an eigenvalue greater than 1.0 and with four or more items loading on it.

The seven factors in the 2006 reference year are, in decreasing order of explanatory power:

- **Physical:** Dynamic Strength, Manual Dexterity, Stamina, *etc.*
- **Equipment:** Operation Monitoring, Technology Design, Troubleshooting, *etc.*
- **Supervision:** Coordinating Work of Others, Developing/Building Teams, Monitoring Resources, *etc.*
- **Awareness:** Night Vision, Operate Vehicles, Sound Localization, *etc.*
- **Perception:** Flexibility of Closure, Perceptual Speed, Selective Attention, *etc.*
- **Interpersonal:** Cooperation, Stress Tolerance, Social Orientation, *etc.*
- **Initiative:** Initiative, Innovation, Persistence, *etc.*

We identified two measures of IT use to assist in examining skill biased technical change. Our proxy for IT technology use in an occupation is the aforementioned item 4.A.3.b.1 "Interacting with Computers." We divide this item into quartiles each year based on the Importance measure. We also use a measure of industry IT Intensity. Aggregated at the BEA industry code level, IT Intensity measures a within-year standardized index of the ratio of IT per full-time-equivalent employee (Stiroh, 2002). Sixty (out of sixty-five) BEA industries were matched to eighty-seven (out of eighty-nine) OES industries; in most cases BEA matched OES one-to-many, but in three cases BEA values were averaged to match OES.[1] The (gross) capital service flow is calculated using the gross operating surplus within an industry, calculating the rate of return on all assets (then multiplied by asset-specific stocks to generate a flow value), and then adding back asset specific depreciation for the year in each industry. The resulting capital flow value is divided by the number of full-time-equivalents of employment, and this value is used to assign each industry to a quartile of IT Intensity.

We measure the wage impacts of skill biased technical change by using hedonic regression. Hedonic regression uses observed prices (in this case, real wages) as the dependent variable and service features as the explanatory variables (in this case, skill factors). The coefficients represent the aggregate marginal willingness to pay for these skills. By construction, the factor scores are in the same scale (mean zero and variance one) and orthogonal to one another, allowing for direct comparisons across skills and across time. We use the set of principal component factor scores from 2006 as the explanatory variables throughout the analysis, with the following empirical model for $F = 7$ factors:

$$RealWage_{i,t} = \beta_0 + \left(\sum_{f=1}^{F} \beta_f \cdot Score_{f,i,t} \right) + \varepsilon_{i,t}$$

One challenge posed by the OES data is that very high wages are censored to preserve respondents' privacy. Each year has a threshold wage that censors approximately 8% of the 50th percentile observations and 11.5% of the 90th percentile observations. We can (1) use a Tobit estimator which is

[1] The two unmatched OES industries are the government and the Postal Service.

robust to censoring, (2) replace the censored values with some function of the threshold, or (3) discard the censored observations. The wage data do not meet the distributional assumptions of the Tobit estimator, and we prefer not to transform the data to make it fit because that would complicate interpretation of the coefficients. Since highly paid occupations are economically important, we chose to retain these observations and replace the censored wages with 150% of the threshold, a method also used by AA in prior analyses.

Summary statistics for the median wages are reported in Table 1, weighted by employment. The minimum and maximum are not reported because these are bounded from below by minimum wage and from above by the OES censoring threshold. As the table shows, on average, occupations with high requirements for **Physical** skills are paid less than others, while those with high requirements for **Equipment, Supervision,** or **Initiative** are paid more. While all of the wages have changed between 2006 and 2014, these changes have been less than one standard deviation.

Table 1. Summary statistics for median wages.

	2006		2014	
	Mean	Standard Deviation	Mean	Standard Deviation
Overall	$15.56	$7.93	$15.60	$8.47
Occupations requiring the top quartile of skill factor…				
Physical	$13.06	$6.49	$12.86	$6.61
Equipment	$22.26	$8.72	$22.88	$9.52
Supervision	$22.36	$8.63	$22.42	$9.51
Awareness	$14.19	$5.27	$14.06	$5.59
Interpersonal	$15.30	$7.46	$15.27	$7.86
Perception	$18.23	$8.20	$18.42	$8.63
Initiative	$21.73	$6.85	$22.11	$7.44

Table 2 shows cross-tabulations of 2014 employment by computer use and IT intensity, showing that the industries with the lowest IT intensity tend to employ the most people. Each cell is the sum of employment reported by OES for all occupation-industry observations matching the specified quartiles in 2014 *and* having employment data in 2006. The latter condition ensures this sample matches the one used in Results section below.

Table 2. 2014 employment by computer use and IT intensity.

		Industry IT Intensity Quartile			
		Bottom	Third	Second	Top
Occupation Computer Use Quartile	Top	7,772,320	2,455,250	736,480	1,534,270
	Second	2,594,890	4,548,210	5,843,980	819,520
	Third	4,375,770	802,300	530,520	737,990
	Bottom	5,422,500	627,020	3,015,740	1,663,680

Results

Hedonic Wage Regression

We begin our empirical investigation of skill biased technical change by constructing a system of hedonic wage regressions using our set of skill factors to explain wages. To look beyond median wages, we run the model using the 10^{th}, 50^{th} and 90^{th} percentiles of each occupation's wages as dependent variables. For example, $RealWage_{i,t}$ is set to the 10^{th} percentile statistic in 2006 for Model I(a), the 50^{th} percentile statistic for Model I(b) and the 90^{th} percentile statistic for Model I(c). This allows us to detect effects that might apply only to atypical members of the occupation. To focus on the most important drivers of wages, we weight each observation by the number of people in that occupation/industry cell that year. We correct for the high degree of correlation of wages within an occupation by clustering the regression errors by occupation. The results of these factors' effects are reported in Table 3.

Table 3. Hedonic effects of 2006 factors on wages in 2006 and 2014.

Model	I(a)	I(b)	I(c)	II(a)	II(b)	II(c)
Dependent Variable	2006 Wage per Hour			2014 Wage per Hour (in 2006 dollars)		
Wage Percentile	10^{th}	50^{th}	90^{th}	10^{th}	50^{th}	90^{th}
Physical	-1.448*** (0.301)	-2.852*** (0.461)	-4.966*** (0.788)	-1.490*** (0.335)	-3.225*** (0.518)	-5.705*** (0.867)
Equipment	1.160*** (0.232)	1.813*** (0.360)	1.934*** (0.594)	1.151*** (0.258)	1.971*** (0.403)	2.288*** (0.629)
Supervision	1.382*** (0.230)	2.321*** (0.378)	4.009*** (0.741)	1.358*** (0.260)	2.417*** (0.403)	4.174*** (0.719)
Awareness	-0.792*** (0.273)	-1.075** (0.434)	-1.489** (0.667)	-0.934*** (0.282)	-1.300*** (0.467)	-1.795** (0.704)
Interpersonal	-0.138 (0.314)	-0.600 (0.467)	-1.314* (0.703)	-0.064 (0.328)	-0.589 (0.507)	-1.323* (0.776)
Perception	1.124*** (0.281)	1.640*** (0.438)	1.921*** (0.734)	1.099*** (0.291)	1.715*** (0.466)	2.062*** (0.755)
Initiative	1.961*** (0.213)	3.637*** (0.365)	6.954*** (0.770)	1.761*** (0.224)	3.616*** (0.362)	7.023*** (0.708)
Constant	12.380*** (0.308)	19.448*** (0.488)	31.207*** (0.834)	12.398*** (0.340)	19.675*** (0.536)	31.916*** (0.887)
R-squared	0.539	0.593	0.585	0.489	0.590	0.603

N = 8,712. Standard errors in parentheses, clustered by 514 occupations. Observations included only if occupation-industry cell exists in both years, weighted by employment in the cell. *** p<0.01, ** p<0.05, * p<0.1.

The wage differences seen in the summary statistics of Table 1 survive the more rigorous test in Table 3. Models I and II are constructed so that a factor's coefficient is the marginal wage impact of increasing the factor score by one standard deviation. For example, for two occupations in 2014 that are otherwise identical with one having a **Supervision** score one standard deviation higher than the other, the 10^{th} percentile of the supervisory-intensive occupation would pay \$1.36/hour more than the 10^{th} percentile of the comparable occupation, the median would pay \$2.42/hour more and the 90^{th} percentile would pay \$4.17/hour more. As a second example, for two occupations in 2006 that are otherwise identical with one having a **Physical** score one standard deviation higher than the other, the 10^{th} percentile of the physical-intensive occupation would pay \$1.45/hour less than the comparable occupation, the median would pay \$2.85/hour less and the 90^{th} percentile would pay \$4.97/hour less.

Our results are consistent with the concept of several skills being independent determinants of wages, rather than a unidimensional spectrum of occupations from "low skill" to "high skill." Occupations with high requirements for **Equipment**, **Initiative**, **Perception** and **Supervision** are associated with higher wages across all wage groups, while **Physical** and **Awareness** skills are associated consistently with lower wages (*cf.* DiNardo & Pischke, 1997). Furthermore, over time the wage effects of skills, positive or negative, are growing in magnitude for the 50^{th} and 90^{th} percentiles.

Evidence of Skill-Biased Technical Change

Having established that these seven dimensions of skill have distinct implications for wages, we are now prepared to investigate the SBTC associated with each skill. The most straightforward test of SBTC is to measure if the level of computer use in an occupation affects its wages. Figure 1 shows an overall effect that is substantial and persistent over time: occupations in the bottom half of IT use are paid much less and are losing ground. This is consistent with the results of Krueger (1993) more than two decades prior. However, it is important to note that the fact that computer use is, on average, associated with higher and rising wages is not proof that the relationship is causal. Some other characteristic, such as cognitive skill or information processing work, may be correlated with computer use and driving the increased compensation (Dinardo and Pischke, 1997)

To dig deeper, we perform hedonic wage regression on each quartile of occupational IT use using our 2006 skill factors as explanatory variables. The results for the 10th and 90th percentiles followed a similar pattern as Models I and II, so we conserve space by reporting only the median results here.

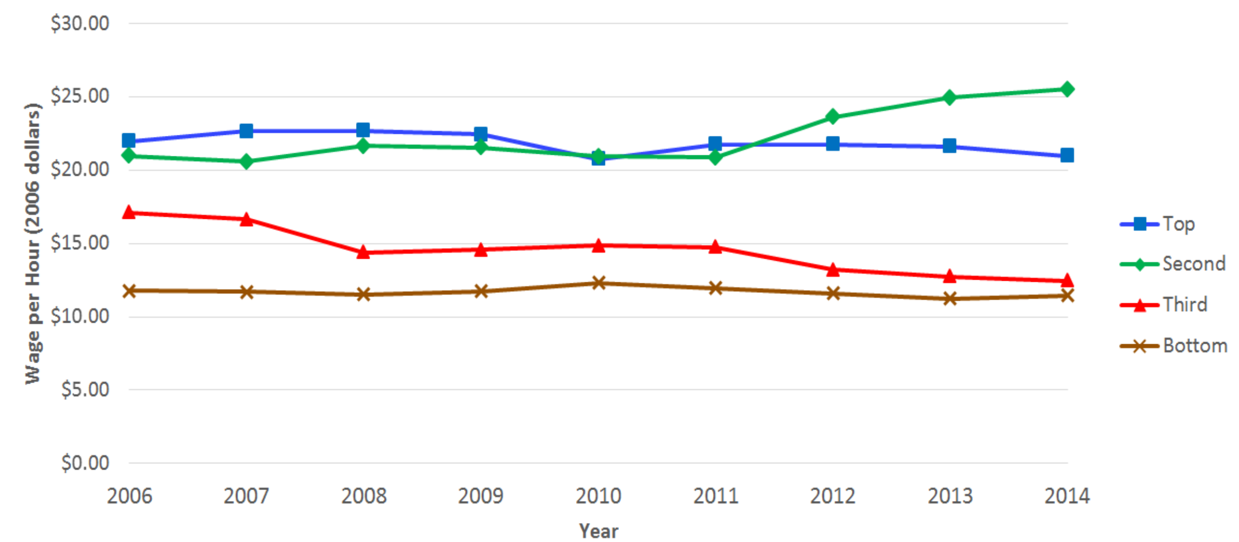

Figure 1. Median wages, by quartiles of computer use.

Table 4. Hedonic effect of skill factors on 2006 wages, by quartiles of occupation-level computer use.

Model	III(a)	III(b)	III(c)	III(d)
Computer Use	Bottom Quartile	Third Quartile	Second Quartile	Top Quartile
Dependent Variable	2006 Median Wage per Hour			
Physical	0.287 (0.673)	-2.026*** (0.657)	-2.374** (1.047)	-0.221 (1.861)
Equipment	1.167*** (0.326)	1.489** (0.675)	2.176*** (0.608)	3.212*** (0.716)
Supervision	0.540 (0.438)	1.828*** (0.638)	3.320*** (0.578)	3.117*** (1.010)
Awareness	0.679*** (0.209)	-2.152*** (0.647)	-0.421 (1.128)	-4.158 (2.970)
Interpersonal	-0.756** (0.334)	-0.959 (0.958)	-0.168 (0.851)	-3.829*** (0.724)
Perception	0.484 (0.299)	2.661*** (0.626)	0.652 (0.892)	0.935 (1.149)
Initiative	1.677*** (0.359)	4.577*** (0.758)	4.445*** (0.833)	3.394*** (1.125)
Constant	12.509*** (0.836)	20.462*** (0.936)	19.786*** (0.822)	22.329*** (1.568)
Observations	2,066	1,777	2,037	2,832
R-squared	0.491	0.678	0.574	0.593

Standard errors in parentheses, clustered by occupation. Observations weighted by employment in occupation-industry cell. *** p<0.01, ** p<0.05, * p<0.1.

Table 4 uses occupation-industry observations that we split into quartiles of computer use. We weighted each cell by employment to ensure consistent point estimates, and clustered the standard errors by occupation to account for the strong correlation of wages within an occupation.

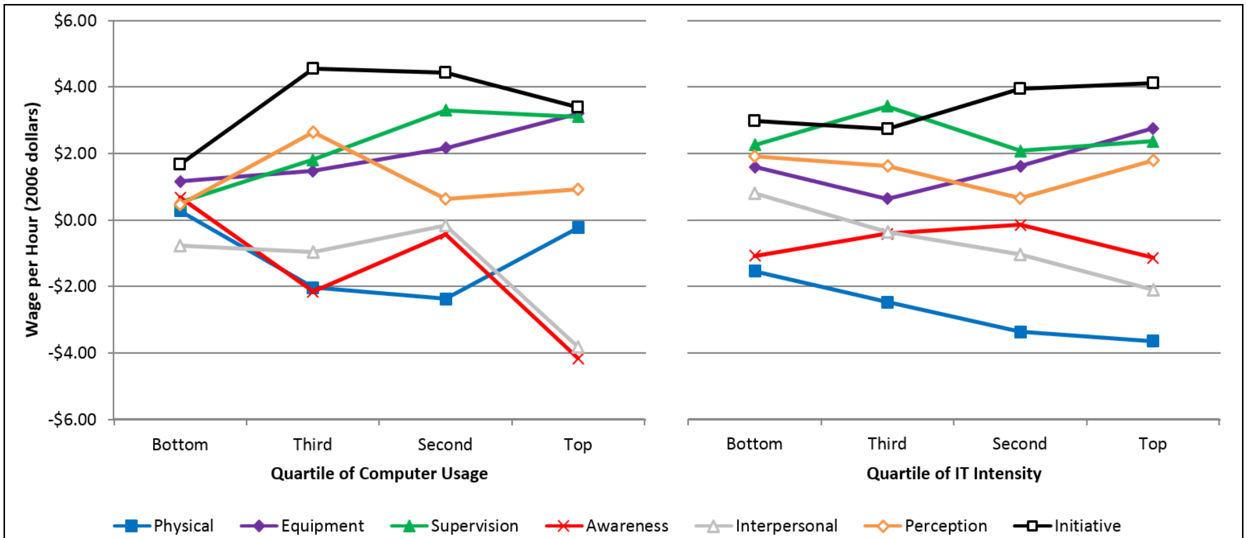

Figure 2. Hedonic effect of skill factors on wages, by quartiles of occupation-level computer use and industry-level IT intensity.

The picture that emerges is considerably more complicated than "certain skills earning more," "computer use leading to higher wages," or "high IT-intensity industries pay more." The regression results of Table 4 are presented graphically in the left panel of Figure 2. The average skill-wage effects seen in Tables 1 and 3 turn out to be aggregations of many different correlations between skills and computer use. Wages for **Equipment** skills increase in computer use. The wage effects of **Initiative**, **Interpersonal** and **Perception** have peaks in the middle of the computer use spectrum. The effect of **Supervision** plateaus in that it increases up to a point of computer use then remains fairly steady. The wage effect of **Awareness** seems orthogonal to computer use (the top-quartile effect looks low but is not statistically significant). **Physical** skills have a U-shaped impact on wages, falling as computer use rises and then rising dramatically for high computer use. Compared to other top-quartile computer use occupations, biomedical engineer is a relatively **Physical** occupation with a score of +0.722.

The effects on matched occupations in 2014 are shown in Table 5. Notable differences between 2006 and 2014 include a magnification of **Supervision**'s and **Initiative**'s wage complementarity with computer use (Sidak-corrected comparison between Models III and IV yield $F_{(4,8680)} \approx 93.99$ and 19.26, respectively) and the penalties for **Interpersonal** skill in low-computer and high-computer occupations have softened to insignificance ($F_{(4,8680)} \approx 48.80$), all of which point to an increase in the value of combining human skills with computer use. In addition, **Perception** appears better compensated overall, but the U-shape for **Physical** skills has become deeper ($F_{(4,8680)} \approx 14.59$ and 60.04, respectively).

One does not need to use a computer directly to feel the impact of advanced technology on wages and employment. We now step away from the occupation-level measure of computer use and look instead at the employing industry's IT intensity. Table 6 uses occupation-industry observations that we split into quartiles of industry IT Intensity. We again cluster the standard errors by occupation to account for the strong correlation of wages within an occupation.

We present our regression results for Model V in Table 6 below along with a graphical representation in the right panel of Figure 2 above. High industry IT intensity is associated with higher wages for **Equipment** and **Initiative** as well as lower wages for **Interpersonal** and **Physical**. For other skills wages are tied more closely to occupations than industries. The impacts of industry IT intensity on 2014 wages in Table 7 are similar to 2006 except the industry effect upon **Physical** has grown stronger ($F_{(4,8680)} \approx 45.29$) as well as the effect upon **Supervision** outside of the bottom quartile ($F_{(3,8680)} \approx 72.88$). The overall increase in compensation for **Perception** in Table 5 is evident as well ($F_{(4,8680)} \approx 24.27$).

Table 5. Hedonic effect of skill factors on 2014 wages, by quartiles of occupation-level computer use.				
Model	IV(a)	IV(b)	IV(c)	IV(d)
Computer Use	Bottom Quartile	Third Quartile	Second Quartile	Top Quartile
Dependent Variable	2014 Median Wage per Hour (in 2006 dollars)			
Physical	0.103 (0.664)	-2.332** (1.128)	-4.709*** (1.454)	-2.561 (2.293)
Equipment	1.706*** (0.442)	-0.745 (1.012)	2.472*** (0.890)	3.536** (1.717)
Supervision	1.551*** (0.567)	0.805 (0.742)	4.219*** (0.523)	3.762*** (1.332)
Awareness	0.814*** (0.264)	1.271 (1.145)	-2.477** (1.002)	-0.678 (2.820)
Interpersonal	-0.191 (0.275)	0.013 (1.104)	-0.037 (0.638)	-2.128 (1.369)
Perception	1.469*** (0.437)	7.976*** (2.228)	1.488 (1.360)	4.497*** (1.621)
Initiative	1.939*** (0.424)	3.071*** (0.980)	5.335*** (0.812)	5.463*** (1.388)
Constant	13.815*** (0.869)	16.166*** (1.509)	19.791*** (1.526)	22.485*** (3.304)
Observations	2,066	1,778	2,037	2,832
R-squared	0.559	0.541	0.622	0.561
Standard errors in parentheses, clustered by occupation. Observations weighted by employment in occupation-industry cell. *** p<0.01, ** p<0.05, * p<0.1.				

Table 6. Hedonic effects of skill factors on 2006 wages, by quartiles of industry IT intensity.				
Model	V(a)	V(b)	V(c)	V(d)
Computer Use	Bottom Quartile	Third Quartile	Second Quartile	Top Quartile
Dependent Variable	2006 Median Wage per Hour			
Physical	-1.553*** (0.539)	-2.481*** (0.519)	-3.379*** (0.620)	-3.658*** (0.730)
Equipment	1.589*** (0.451)	0.629 (0.415)	1.602*** (0.434)	2.744*** (0.597)
Supervision	2.250*** (0.513)	3.411*** (0.499)	2.074*** (0.525)	2.364*** (0.633)
Awareness	-1.089** (0.500)	-0.427* (0.226)	-0.157 (0.751)	-1.152* (0.630)
Interpersonal	0.780 (0.524)	-0.368 (0.408)	-1.060* (0.611)	-2.122*** (0.664)
Perception	1.915*** (0.536)	1.617*** (0.344)	0.639 (0.688)	1.783*** (0.612)
Initiative	2.979*** (0.617)	2.723*** (0.269)	3.941*** (0.602)	4.105*** (0.683)
Constant	16.871*** (0.555)	19.257*** (0.536)	18.631*** (0.658)	20.408*** (0.648)
Observations	2,390	1,940	2,462	1,901
R-squared	0.579	0.647	0.536	0.631
Standard errors in parentheses, clustered by occupation. Observations weighted by employment in occupation-industry cell. *** p<0.01, ** p<0.05, * p<0.1.				

Table 7. Hedonic effects of skill factors on 2014 wages, by quartiles of industry IT intensity.				
Model	VI(a)	VI(b)	VI(c)	VI(d)
Computer Use	Bottom Quartile	Third Quartile	Second Quartile	Top Quartile
Dependent Variable	2014 Median Wage per Hour (in 2006 dollars)			
Physical	-1.671*** (0.629)	-3.223*** (0.502)	-4.344*** (0.566)	-5.201*** (0.696)
Equipment	1.156 (0.704)	0.008 (0.567)	2.210*** (0.728)	3.031*** (0.880)
Supervision	2.104*** (0.657)	3.879*** (0.497)	2.689*** (0.496)	3.400*** (0.620)
Awareness	-0.463 (0.544)	0.403 (0.605)	0.649 (0.598)	-0.307 (0.827)
Interpersonal	0.609 (0.567)	-0.618 (0.655)	-0.306 (0.595)	-2.491** (1.001)
Perception	4.720*** (1.065)	5.271*** (1.208)	1.704* (0.925)	3.226*** (1.037)
Initiative	2.922*** (0.603)	2.268*** (0.772)	3.740*** (0.539)	4.812*** (0.934)
Constant	16.218*** (0.950)	15.659*** (0.858)	19.786*** (0.936)	20.951*** (1.251)
Observations	2,390	1,940	2,462	1,901
R-squared	0.569	0.619	0.625	0.654
Standard errors in parentheses, clustered by occupation. Observations weighted by employment in occupation-industry cell. *** p<0.01, ** p<0.05, * p<0.1.				

High Skill Jobs

We have presented evidence that the seven distinct dimensions of skill attract different levels of wages, and that these wages vary with the IT use within an occupation and industry. These wage effects reflect the market-clearing prices for these skills in the labor market. Wages could vary due to changes in supply or demand, manifesting via changes in the skill composition of occupations and changes in the number of people working in each occupation. We are actively investigating supply-side and demand-side effects, but some preliminary results can help to put the wage results in context.

All of the regression tables above report the effects of differences in skill requirements across jobs. The use of z-scores has many useful features but also the unfortunate side effect of masking the absolute magnitude of those differences. Do occupations tend to cluster around the mean? Is there any one dominant skill? It is sufficient in the current economy to master a single skill, or does the labor market disproportionately reward those who excel in multiple areas? We look at these questions by examining which jobs require a skill to be in the top quartile. Table 8 shows that some high-skill jobs are more common than others; otherwise every cell would show 25%. The most striking statistic is that six of every seven jobs require the employee to have top-quartile skills in *something*. Only one seventh of jobs are designed for people whose skills are below the 75^{th} percentile on all skill dimensions. The many people who are merely average at all skills may only be eligible for the lowest-paying jobs in the economy.

Figure 3 shows that there is a wage premium for bringing at least two high skills to the labor market.

Table 8 shows a slight increase in employment share between 2006 and 2014 in jobs that require high **Supervision** skills and a slight decrease in **Awareness**-intensive ones ($t \approx 133.12$ and 111.40, respectively). The proportions of people employed in other high-skill jobs have shifted by statistically significant but economically unimportant amounts, providing preliminary evidence that the labor market has responded to the Great Recession largely through pricing (wage levels) rather than the mix of labor types employed.

Table 8. Share of employment requiring top quartile of skill.		
	2006	2014
Physical	39.04%	39.18%
Equipment	12.73%	12.71%
Supervision	12.62%	13.30%
Awareness	13.12%	12.56%
Interpersonal	43.17%	42.81%
Perception	23.71%	23.33%
Initiative	15.85%	15.71%
At least one top quartile	86.20%	85.98%

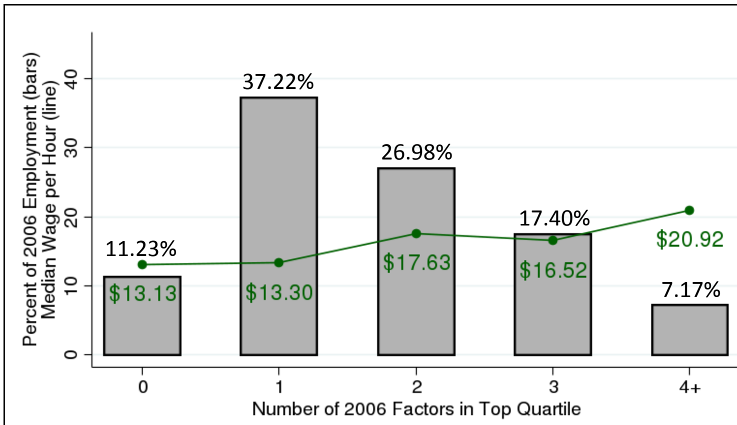

Figure 3. Top quartiles required for occupations. Top quartiles required for occupations and median wages. Percentages and wages weighted by employment.

Discussion and Conclusion

The wages paid for skills, as revealed via hedonic regression, have changed over time. Some of these changes are associated with computer use. When discussing SBTC, it is critical to understand *which* skills are associated with use of advancing technology. We have identified several dimensions of skill with economically important impacts on wages. None of them is a proxy for a unidimensional "low skill to high skill" measure, and each of them has a different pattern of effects from computerization.

We find that **Equipment** and **Supervision** skills appear to be most rewarded when associated with increased computer use, with the effect increasing over time for the latter. Our results show that **Initiative**, **Interpersonal**, and **Perception** are complemented by an optimal level of IT use to complement these skills, not simply that more is better. **Physical** skills have a strange relationship with IT; they are generally best compensated where IT is implemented least (*e.g.*, gardeners and trolley operators), but can also provide the small push that makes cutting-edge IT truly valuable (*e.g.*, biomedical engineers).

Wages paid for **Equipment** and **Initiative** skills appear to increase when employed by industries with high IT intensity per capita, while **Interpersonal** and **Physical** skills appear to decrease in those same industries. AA show that on average, **Physical** skills have not been well-compensated for a long time, and the situation has grown even worse between 2006 and 2014. Overall, **Initiative** has been the most durable in terms of earning power. In an era of rapid change, adaptability and initiative can be perhaps the most valuable attributes one can bring to the market.

The **Awareness**, **Interpersonal** and **Supervision** skills represent capabilities that have thus far resisted automation. While technologies have appeared that are complementary to **Supervision** (*e.g.*, enterprise dashboards) and are just emerging to complement **Awareness** (*e.g.*, heads-up displays for cars), they have yet to progress beyond a poor substitute for **Interpersonal** skills. Does a recording of "Your call is very important to us" improve or worsen a customer's attitude toward the human customer service representative who eventually speaks with that customer? With the large number of people employing **Interpersonal** skills in their jobs, this seems to be a need for technical change biased toward this particular skill.

There is precedent for such an adjustment, but only when the supply and demand of skills get seriously out of balance. Directed technical change theory (Acemoglu, 1998) predicts that entrepreneurs have an incentive to develop technologies that vacuum up the glut of **Interpersonal** skill and turn it into something more "productive." However, this process can take a decade or more to reach a new equilibrium. Prior to equilibrium, the oversupplied skill passes through a phase of depressed wages. If we lower our standard from "productive" to "monetized," then we already have a technology in which **Interpersonal** skill can shine: social media. However – outside of a few YouTube superstars (Lewis,

2013) and high-priced social media executives – it is unclear that social media is a path to prosperity, and it is unreasonable to expect people to invest in a skill that *might* become valuable in a decade.

Our findings have important implications for the study of SBTC. The complex and non-linear interactions between technology use and skill mean that univariate measures of skill or simple econometrics on skill categories are not sufficient to understand the dynamics of technology's effects on different skills. For example, average effects of technology on wages masked changes that ran opposite to each other for different skills. The use of interaction terms is not sufficient to capture this diversity. Relatedly, characterizing skills as dimensions provides deeper insights than considering occupations to reside in mutually exclusive categories.

The complex interactions between skills and technology also call for finer targeting of reskilling interventions than urging workers to earn a college degree. A first-order criterion for targeting is those occupations that have a large fraction of long-term unemployed because this is evidence either of severe oversupply, a mismatch between employer needs and employee skills, or both. A second-order criterion is to target who may be misallocated in the labor market, as evidenced by offering discounted skills and helping them move to occupations or industries that value their skills more highly.

Our analysis indicates that the following segments of the labor market have discounted skills:

- High-**Interpersonal** jobs in high-Computer occupations or high-IT-intensity industries,
- High-**Physical** jobs in mid-Computer occupations or high-IT-intensity industries, and
- Any job that scores very low in a cell that has a particularly high coefficient.

Although these jobs will never go to zero, reallocating some of their employees would appear to increase the overall efficiency of the labor market. Reallocating these employees can be as simple as transitioning them to into similar occupations in other industries. However, the relentless march of technology means that this is only a temporary measure. Before long, it is likely that the vast majority of industries will rise to what is today considered high IT intensity, and more jobs will be either complemented or substituted by rapidly advancing technology capabilities. This means that a more lasting solution to misallocated labor is acquiring new skills to compete.

Five sixths of all jobs in the economy require employees to possess the top quartile of skill in *something;* technological de-skilling might let humans concentrate on fewer skills but not ignore them entirely. The labor market also seeks those who excel in more than one skill (see also Lee, 2013) and pays them accordingly. In other words, "there's never been a worse time to be a worker with only 'ordinary' skills and abilities to offer." (Brynjolfsson & McAfee, 2014). Note, however, that "college" is not a skill, and in particular the skill called Initiative does not necessarily require training. Many people may be able to increase their wages by moving to an occupation that values **Initiative**, if such a move is possible for them.

Future work can look beyond the summary statistics of wages and employment levels to investigate further the multidimensional nature of workforce skills and study how computers and IT affect the benefits and costs of working in specific occupations. There have been unexpected changes in occupations such as journalists and librarians even when the core educational requirements of the occupation have not changed (Boudreau *et al.*, 2014). Future changes in work are can be better understood by using a multidimensional set of skill measures, such as the one explored in this paper.

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Appendix

Acemoglu & Autor (2010) and Card & DiNardo (2002) used data from the US Census Current Population Survey (CPS), with observations sampled at the individual level. Some of those data have been anonymized and made easily available to researchers at www.ipums.org. We ran our analysis using IPUMS data to ensure that our results are not idiosyncratic to BLS data. One *advantage* of the CPS data is that we can calculate percentiles directly from entire occupations, rather than piecing them together from occupation-industry cells and correcting the standard errors with clustering. Two *disadvantage* are that (1) Census and BLS aggregate occupations and industries so differently that the matching procedure mutes much of the variation in our skills data, and (2) CPS respondents often fail to report wages. We follow prior literature by excluding observations with the Census Bureau's estimated wage. These disadvantages combine to make the CPS estimates less precise than the BLS estimates in the main paper. The CPS results are broadly similar to ours for the 10th and 50th percentiles, except that we show the hedonic effect of Awareness centered at roughly minus one dollar while CPS shows it centered at roughly zero. Some of the CPS results are more extreme for the 90th percentile due to differences in censoring. Table A1 below replicates Table 3 using the CPS data.

Table A1. Hedonic effects of 2006 factors on CPS wages in 2006 and 2014.

Model	I(d)	I(e)	I(f)	II(d)	II(e)	II(f)
Dependent Variable	2006 Wage per Hour			2014 Wage per Hour (in 2006 dollars)		
Wage Percentile	10th	50th	90th	10th	50th	90th
Physical	-1.227*** (0.195)	-2.659*** (0.416)	-6.386*** (0.967)	-1.734*** (0.260)	-3.846*** (0.623)	-9.918*** (1.373)
Equipment	0.712*** (0.227)	1.323*** (0.485)	0.257 (1.128)	1.070*** (0.304)	2.172*** (0.727)	1.580 (1.602)
Supervision	0.544*** (0.180)	1.296*** (0.384)	3.530*** (0.894)	0.729*** (0.243)	1.810*** (0.582)	4.809*** (1.283)
Awareness	-0.041 (0.184)	0.053 (0.393)	0.076 (0.914)	-0.058 (0.250)	0.027 (0.598)	0.443 (1.318)
Interpersonal	0.240 (0.232)	0.782 (0.495)	1.241 (1.152)	0.432 (0.310)	1.514** (0.742)	2.626 (1.636)
Perception	1.163*** (0.223)	1.726*** (0.476)	1.849* (1.107)	1.476*** (0.298)	2.451*** (0.714)	2.361 (1.573)
Initiative	1.124*** (0.215)	2.438*** (0.458)	5.233*** (1.065)	1.515*** (0.287)	3.003*** (0.686)	6.087*** (1.512)
Constant	8.777*** (0.184)	17.634*** (0.392)	33.945*** (0.913)	11.435*** (0.246)	23.594*** (0.590)	46.166*** (1.300)
R-squared	0.397	0.366	0.303	0.416	0.344	0.310

N = 248. Standard errors in parentheses. Observations are percentiles of CPS wage data for each occupation using CPS sample weights, with the occupations themselves included only if present in both years and weighted by the sum of sample weights within that occupation. *** p<0.01, ** p<0.05, * p<0.1.