How Does Technology Affect Skill Demand? Technical Changes and Capital-Skill Complementarity in the 21st Century

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Abstract— **This paper attempts to examine technology's impact on the labor market through the lens of skilled labor. Technical changes in the late 20th century are skill-biased in nature, because they are found to complement with skilled labor who are adept at adopting new technologies. However, recent studies document a lower demand for high-skilled labor in the 21st century, compared with the late 20th century. Are technologies starting to substitute for human skills instead of complementing them? Drawing on the wage share data from 1975 to 2015 for 18 sectors in the United States, I find strong and robust evidence of complementary relationships between technical changes and demand for skilled labor. Furthermore, my results suggest that technologies have become more skilled-biased, not less, in the 21st century.**

I. Introduction

This paper aims to shed light on the the relationship between technological changes, capital and skill demand in the 21st century. It attempts to explore how recent technological changes affect the demand for skilled labor, and how that relationship varies over time and across industries.

The concern over new technologies destroying jobs is not a new one. Numerous scholars have expressed concerns over the impact of recent technological changes on the labor market. In his 2014 book *The Second Machine Age,* Brynjolfsson argues that while the Industrial Revolution, or First Machine Age, is all about power systems to augment human muscle, in the Second Machine Age we are beginning to automate a lot more cognitive tasks, a lot more of the control systems that determine what to use that power for. According to Brynjolfsson, computerized machines nowadays are so smart and powerful that they will start substituting for skilled human labor rather than complementing it.

Along these lines, Karabarbounis and Neiman (2013) study labor market data in 59 countries from 1975 to 2012 and observe downward trends in the labor share for 42 of them. These findings lead to a widespread concern that the relationship between capital and skill is changing in the 21st century, as machines start replacing human labor at the top of the skill distribution. Do recent technological changes challenge the capital-skill complementarity assumption?

There is also empirical evidence revealing a lower demand for skilled labor within the last decade. Economists frequently characterize information and communication technologies (ICT) in the 21st century as skill-biased in nature because they favor skilled workers who are suitable to adopt new technologies over unskilled ones. However, some recent studies find evidence against the complementary relationship between technologies and skilled labor. Beaudry et al. (2013), using data from the Outgoing Rotation Group Current Population Survey Supplements for the years 1979-2011, document a decline in the demand for cognitive tasks and highly-educated workers from 2000 to 2010. Is this reversion temporary, or does it signify a change in the skill-biased nature of technological changes?

This paper answers the two questions above with a dataset covering the years 1975 to 2015. The rest of the paper is organized as follows: Section II reviews studies relevant to this subject. Section III explains economic of the capital and labor market. Section IV describes empirical models estimated in the paper. Section V presents data and summary statistics. Section VI summarizes empirical results. Section VII concludes and points out areas for future studies.

II. Literature Review

A. A Capital-Skill Complementarity

The role of skill and education in a production function was tested first by Griliches almost 40 years ago (Griliches 1969). Drawing on post-World War II data from U.S. manufacturing sectors, Griliches finds a positive relationship between capital employment and skill demand. He formalizes this phenomenon as capital-skill complementarity, a hypothesis stating that physical capital is more complementary to skilled labor than to unskilled labor. Fallon and Layard (1975) confirm this hypothesis with data at both aggregate and sectoral levels.

However, capital and skilled labor have not always been complements. Studies drawing on data from the late 19th century reveal evidence to the opposite. Cain and Paterson (1986) examine the U.S. manufacturing sector from 1850 to 1919 and find that physical capital complements with raw materials and substitutes for skilled labor. In the same vein, James and Skinner (1985) divide manufacturing sectors in the 1850s into skilled and less skilled sectors. They find strong complementary relationship in the skilled sector but relative substitutability in the remaining sectors.

Summing up, while post-World War II data reveals a complementary relationship between capital and skill, in the late 19th century capital is found to substitute for skilled labor at industry levels.

B. Skill-Biased Technical Change (SBTC)

1) Evidence for the United States: After capital-skill substitutability in the 19th century and capital-skill complementarity in the mid 20th century, the late 20th century is known as a period with growing demand for skilled labor (i.e., skill upgrading). Most studies attribute the accelerated skilled upgrading in the late 20th century to skilled-biased technical change (SBTC). SBTC, also known as the technology-skill complementarity, is a shift in the production technology that favors skilled over unskilled labor by increasing its relative productivity and, therefore, its relative demand (Violante 2008). Unlike the capital-skill complementarity hypothesis, the technology-skill hypothesis supports the complementarity between new capital (e.g., technology-embodied capital) and skilled labor.

The paper of Berman et al. (1994) is among the first studies that examines SBTC empirically. Relying on data drawn from the Annual Survey of Manufactures (ASM) in the 1980s, Berman et al. identify an increasing share of skilled labor in total employment within the 450 industries in U.S. manufacturing. Through an econometric analysis that relates the shift in favor of skilled workers to production-labor-saving technical change, they confirm the SBTC hypothesis. They attribute the increasing wage share of skilled labor in American manufacturing in the 1980s to the level of investment in R&D and computers.

Autor et al. (1998) extend Berman et al.'s study by adding more sectors over a longer period. They link educational wage-bill share data with computer utilization records from the Current Population Survey for years 1960 to 1990. They find a positive relationship between growth in computer usage and skill upgrading for 47 U.S. private industry sectors starting in the 1970s. Although the strong correlation is by no means a causal relationship, their findings are valuable in pointing out that the skill upgrading in the U.S. has been concentrated in the most computer-intensive sectors.

2) International Evidence: Empirical studies outside the United States reveal mixed findings. On the one hand, studies of OECD countries strengthen the SBTC hypothesis. Machin and Reenen (1998) study the changing wage share and employment in seven OECD countries (United States, Denmark, France, Germany, Japan, Sweden, and the United Kingdom). All countries show a shift in relative labor demand in favor of skilled labor and significant complementarity of capital with new technology. In the same vein, Michaels et al. (2010) update the model by categorizing labor into low, middle, and high educated workers. Using a panel dataset covering the U.S., Japan, and nine European countries from 1980-2004, they find strong correlation between the growth in ICT and the growth in the demand for the most educated workers. They conclude that technological changes since the 1980s can account for up to 25% of the growth in the demand for college-educated workers.

On the other hand, countries in the Asia-Pacific region are less influenced by the diffusion of skill-biased technologies. Berman et al. (2003) study the manufacturing sector in India during the 1980s. They find that India does not show significant growth in the demand for skilled labor that is common to other high-income countries. They also find that increased capital investment can explain very little of the increased wage share of skilled labor in Indian manufacturing sectors.

Summing up, countries outside the United States show inconclusive evidence regarding SBTC. Despite a rich body of literature on this topic, there remain few studies on the effect of ICT and capital on the skill demand in the U.S. after 2000. The next section describes a theoretical framework that can be used to test the capital-skill and technology-skill complementarity hypotheses in the 21st century.

III. Theory

At the industry level, the shift away from unskilled to skilled labor can happen between and within industries. In the former case, trade and immigration are likely to cause labor to shift away from less-educated and import-competing sectors. In the latter case, skill-biased technological changes could reduce the demand for unskilled labor and increase the demand for skilled labor within an industry. To explore factors that might explain within-industry changes in the skilled labor's employment share, I start from a firm's cost function. Following the practice of Berman et al. (1994) and Autor et al. (1998), I assume heterogeneity of labor by categorizing it into skilled and unskilled labor groups. I also assume that the firm's capital input is quasi-fixed. [1] Therefore, the firm's variable cost function is

$$CV(W_s, W_u, K, Q) \tag{1}$$

where W_s and W_u are the wage rates of skilled and unskilled labor, K stands for quasi-fixed capital, and Q represents real output.

Drawing on Berman et al. (1994), Machin and Van Reenan (1998), and Meschi et al. (2008), a translog functional form [2] of the variable cost implies

$$\begin{aligned}\ln(CV) = \alpha_0 &+ \sum_{i=s,u} \beta_i \ln(W_i) \\ &+ \sum_{i=s,u} \sum_{j=s,u} \beta_{ij} \ln(W_i) \ln(W_j) + \beta_y \ln(Y) \\ &+ \sum_{i=s,u} \beta_{iy} \ln(Y) + \beta_k \ln(K) + \sum_{i=s,u} \beta_{ik} \ln(K)\end{aligned} \tag{2}$$

where the β parameters denote the effect of factor prices of factor prices, output, and the capital stock over total variable cost. Following Shephard's lemma, the cost-minimizing demand for an input can be derived by differentiating the

[1] Quasi-fixed capital assumes the capital to be fixed in the short-run.

[2] A translog functional form provides a second-order approximation to a Cobb-Douglas production function and does not impose any restriction on the substitutability of various inputs.

cost function with respect to the factor price. Therefore, the share equation for skilled labor can be derived as

$$S_{ti} = \beta_0 + \beta_1 \ln(\frac{W_{sti}}{W_{uti}}) + \beta_2 \ln(\frac{K_{ti}}{Q_{ti}}) + \beta_3 \ln Q_{ti} + \epsilon_{ti} \quad (3)$$

where t indexes year, i indexes industry, and ϵ_{ti} is the error term.

In equation (3), the sign of β_1 depends on whether the elasticity of substitution between skilled and unskilled labor is larger than 1. Estimates of β_2 indicate the relationship between capital and skilled labor: capital and skill are complementary inputs if β_2¿0 and substitutes if β_2¡0. Estimates of β_3 show the relationship between growth in output and the wage share of skilled labor.

To account for the impact of technologies, I augment equation (3) by including a new variable $TECH_{ti}$ to represent technology-embodied capital stock in industry i and year t. The new equation becomes

$$\begin{aligned} S_{ti} = \beta_0 + \beta_1 \ln(\frac{W_{sti}}{W_{uti}}) + \beta_2 \ln(\frac{K_{ti}}{Q_{ti}}) + \beta_3 \ln Q_{ti} \\ + \beta_4 TECH_{ti} + \epsilon_{ti} \end{aligned} \quad (4)$$

where estimates of β_4 denote the relationship between technologies and skill demand. The SBTC hypothesis suggests the sign of β_4 to be positive.

IV. Empirical Models

In empirically estimating the skilled labor's wage share, the wage share variable $\frac{W_{sti}}{W_{uti}}$ is frequently removed from the model because it is likely to be highly endogenous (Machin and Reenen 1998). Assuming (i) complete mobility of employees across industries and (ii) that wage differentials are fully absorbed by industry dummy variables, I include fixed effects to capture any unobserved heterogeneity between industry that is time-invariant (D_i). Equation (4) becomes

$$\begin{aligned} S_{ti} = \beta_0 + \beta_1 \ln(\frac{K_{ti}}{Q_{ti}}) + \beta_2 \ln Q_{ti} + \beta_3 TECH_{ti} \\ + \epsilon_{ti} + D_i \end{aligned} \quad (5)$$

Most studies in the early 1990s proxy the stock of technology by the ratio of employees using computers at work. Of course, this is hardly a good measure of technologies in the 21st century due to the variety of electronic devices employed in the work place. Later studies frequently use investment in research and development (R&D) instead. However, R&D is recorded separately from software purchases and is not the best variable to measure the technology stock either. In this paper, I choose to use the stock of intellectual property products from the Bureau of Economic Analysis (BEA) that is comprised of R&D, software, and originals work to get a more complete account of firm's technology stock. Admittedly, this is not the most accurate measure of technology because it contains the stock of entertainment, literary, and artistic originals at the industry level. However, because R&D and software data is not available for industries of interest separately, the stock of intellectual property products is the best measurement available to proxy for an industry's technology stock. I adjust the variable (IPP_{ti}) by output and take the log transformation for a consistent specification on the right-hand side of the equation, giving the final equation:

$$S_{ti} = \beta_0 + \beta_1 \ln(\frac{K_{ti}}{Q_{ti}}) + \beta_2 \ln Q_{ti} + \beta_3 \ln(\frac{IPP_{ti}}{Q_{ti}}) + \epsilon_{ti} + D_i \quad (6)$$

Table 1 summarizes estimates of β_3 in two relevant studies. Despite the disparity in measurements of capital or selections of industries, both papers document positive estimates of β_3 in the U.S. from 1960 to 1980. Both findings indicate the complementary relationship between capital and skilled labor and the presence of skill-biased technological change. Using a similar framework, this paper reexamines the value of β_3 in 18 U.S. industries from 1975 to 2015.

Table 1: Estimates of β_3 in Relevant Studies

	Berman et al., 1994	Autor et al., 1998	
Measurement	Capital Stock	Five-year sum of real investment	
Industry	Manufacturing	Manufacturing	41 NIPA Industries
β_3 in the 1960s	0.140	0.149	0.161
β_3 in the 1970s	0.129	0.194	0.318
β_3 in the 1980s	0.389	0.440	0.320

V. Data and Summary Statistics

The data used in this paper comes from two sources. The first is the Current Population Survey March samples from 1975 to 2015. It contains information on annual wage income, weeks worked, and usual hours worked per week, as well as demographical information regarding age, education level, sex, and race for the nearly 8 million individuals surveyed. Following common practice in the field, I limit the dataset to employees within age range 16-64 and who are working full time throughout the year (i.e., working for more than 35 hours per week and more than 40 weeks per year). The second data source is the BEA, which provides 2-digit industry level data on (1) real output, (2) stock of private intellectual property products, and (3) stock of equipment and structures.

A. Crosswalk between CPS and BEA

In this paper, I consider 18 private sectors that are mapped between the CPS and the BEA. The $ind1990$ variable in the CPS provides a set of industry codes from 1968 forward that are consistent with the North American Industry Classification System (NAICS) used in the BEA datasets. (Refer to the Appendix for the exact crosswalk between two sources.)

B. Wage Share

I categorize employees as either skilled or unskilled based on their education background. The education background indicates an individual's level of expertise and is a good proxy for the skill level. Those who have obtained a bachelor's or more advanced degree (master's, professional school, doctorate degrees, etc.) are categorized as skilled labor.[3] The remaining employees are classified as unskilled labor, whose education levels range from no degree to high school diploma and associate's degree. The wage share variable is then derived as the ratio between the sum of the skilled labor's wage income and total wage income. Table 2 displays the skilled labor group's average wage share in 10-year intervals for the industries under analysis. The average share grows from 19% in 1975-85 to 39% in 2005-15, an upward trend that is well-documented.[4] Disparities remain in the changes of wage share for different sectors. For sectors such as finance and chemical products the wage share ratio is always high (around 40%). Sectors such as electrical products and paper products experience the largest percentage growth, the ratio of which grows from 28% to 62% and from 10% to 45%, respectively. The ratio remains low for sectors such as wood and and plastics product across decades.

Table 2: High Education Wage Share

	1975-1985	1985-1995	1995-2005	2005-2015
Wholesale trade	0.279	0.328	0.396	0.460
Retail trade	0.162	0.213	0.260	0.304
Transportation	0.120	0.172	0.219	0.252
Finance and insurance	0.404	0.494	0.595	0.686
Wood	0.107	0.112	0.156	0.196
Furniture	0.088	0.146	0.167	0.218
Nonmetallic products	0.147	0.198	0.249	0.266
Metal	0.159	0.179	0.218	0.243
Machinery	0.229	0.330	0.397	0.481
Electrical products	0.276	0.393	0.495	0.618
Motor vehicles	0.208	0.290	0.352	0.467
Food, beverage and tobacco	0.142	0.239	0.322	0.377
Textile mills	0.123	0.178	0.218	0.316
Apparel and leather products	0.131	0.151	0.270	0.353
Paper products	0.103	0.215	0.215	0.452
Printing activities	0.262	0.348	0.430	0.505
Chemical products	0.367	0.452	0.540	0.573
Plastics and rubber products	0.166	0.200	0.250	0.286
Overall	0.193	0.258	0.319	0.392

C. *Explanatory Variables*

To proxy for technological change, I use the stock of intellectual property products from the BEA. It is the best measure of technology stock available at the industry level, as explained in Section IV. The output-adjusted sum of equipment and structure stocks is used to proxy for physical capital. Real output is calculated as nominal output divided by the price level, as documented in the BEA dataset. A statistical summary of all variables used in the paper is reported in the Appendix.

VI. Empirical Results

A. *Benchmark Model*

Table 3 reports a set of fixed-effects regressions covering the four time periods 1975-1985, 1985-1995, 1995-2005, and 2005-2015. It estimates the change in the skilled labor share of wage bill on indicators of changes in physical capital, intellectual property products, and real output.

Model 1 includes only time dummies for time periods 1985-1995, 1995-2005, and 2005-2015. Coefficients have positive signs, which indicate a continued growth of skilled labor share of wage bill through the early 21st century. Model 2 estimates the share equation (6) and shows a significant and positive relationship between skill demand and capital stock. According to the model estimates, a one percent increase in physical capital will lead to a 0.11% increase in skilled labor wage share, and one percent increase in technology-embodied capital will lead to a 0.02% increase. The positive coefficients support the skill-capital and skill-technology complementarity hypotheses. Incidentally, the three independent variables can collectively explain more than 60% of the variations in skill demand. Model 3 in enhances equation (6) by interacting the intellectual property products stock with time dummy variables. Compared with the base period 1975-1985, technological changes appear to be progressively skill biased in the 1990s and afterwards. The interaction term has a positive sign for all three periods and is largest in 2005-2015. This upward trend indicates a stronger relationship between technological changes and demand for skilled labor in the 21st century. In model 4, I interact physical capital with time dummy variables, and the interaction terms have positive though insignificant coefficient estimates. The evidence suggests capital-skill complementarity across all periods, and no significant changes in the complementary relationship in the 21st century.

Summing up, through econometric analysis I find continuously growing demand for skilled labor in the past four decades. The wage share of skilled labor is significantly and positively correlated with the stock of physical capital and intellectual property products, supporting the capital-skill and technology-skill hypotheses. The complementary relationship between technology stocks and capital exhibits an upward trend in the four periods studied.

B. *Robustness Checks*

Table 4 reports tests of robustness to alternative measures of demand for skilled labor. I use the employment share of skilled labor to proxy for skill demand, based on the assumption that wage differentials across industries can be controlled by the fixed-effects estimator. Model 2 again returns positive coefficient estimates. Similar to my results from Table 3, models 3 estimates the interaction terms to be positive, and model 4 estimates them to be positive though insignificant. Therefore, the technology-skill complementarity, capital-skill complementarity, and a trend towards a stronger complementarity relationship between technologies and skilled labor are statistically significant and robust.

C. *Industry-level Evidence*

I next examine how the complementary relationships between skill and capital vary across industries. I create industry dummy variables for all sectors and interact them with

[3]Would different definitions of skilled labor change my estimation results? In this paper I follow the practice of Berman et al. (1994) and Autor et al. (1998) to group college graduates and beyond as skilled labor.

[4]The upward trend is also documented by Berman et al. (1994) and Goldin and Katz (1996).

Table 3: Changes in the Skilled Labor's Wage Share

Model	1	2	3	4
ln(IPP/Y)		0.0230***	0.0071	0.0050
		(0.0056)	(0.0052)	(0.0056)
ln(K/Y)		0.1170***	0.0572***	0.0697***
		(0.0099)	(0.0111)	(0.0116)
ln(Y)		-0.0760***	-0.0417***	-0.06130***
		(0.0118)	(0.0109)	(0.0147)
1985-1995	0.0647***		0.0985***	0.0300
	(0.0056)		(0.0283)	(0.0212)
1995-2005	0.1260***		0.2050***	0.0818***
	(0.0056)		(0.0315)	(0.0234)
2005-2015	0.1990***		0.3260***	0.1310***
	(0.0055)		(0.0289)	(0.0254)
1985-1995			0.0116***	0.00156
Interaction			(0.00412)	(0.0047)
1995-2005			0.0244***	0.0059
Interaction			(0.0049)	(0.0050)
2005-2015			0.0393***	0.0051
Interaction			(0.0047)	(0.0056)
Constant	0.1930***	1.4470***	0.8120***	1.0000***
	(0.0040)	(0.1040)	(0.1110)	(0.1340)
R squared				
Between	0.67	0.64	0.72	0.69
Within		0.22	0.38	0.09
Overall	0.26	0.37	0.48	0.32
No. of Observations	738	738	738	738

Note: T-statistics in parentheses (z-statistics for random effects model). ***Significant at 0.01 level. **Significant at 0.05 level. *Significant at 0.1 level.

Table 4: Changes in the Skilled Labor's Employment Share

Model	1	2	3	4
ln(IPP/Y)		0.00992***	0.000433	-0.00141
		(0.00367)	(0.00334)	(0.00367)
ln(K/Y)		0.0787***	0.0464***	0.0553***
		(0.00648)	(0.00713)	(0.00759)
ln(Y)		-0.0481***	-0.0246***	-0.0380***
		(0.00774)	(0.00698)	(0.00962)
1985-1995	0.0419***		0.0668***	0.0232*
	(0.00372)		(0.0181)	(0.0139)
1995-2005	0.0722***		0.132***	0.0401***
	(0.00372)		(0.0202)	(0.0153)
2005-2015	0.125***		0.227***	0.0763***
	(0.00363)		(0.0185)	(0.0167)
1985-1995			0.00863***	0.00311
Interaction			(0.00269)	(0.00308)
1995-2005			0.0186***	0.00498
Interaction			(0.00316)	(0.00327)
2005-2015			0.0306***	0.00376
Interaction			(0.00302)	(0.00364)
Constant	0.128***	0.908***	0.524***	0.651***
	(0.00263)	(0.0682)	(0.0713)	(0.0879)
R squared				
Between	0.64	0.61	0.72	0.67
Within		0.21	0.34	0.1
Overall	0.19	0.32	0.43	0.27
No. of Observations	738	738	738	738

Note: T-statistics in parentheses (z-statistics for random effects model). ***Significant at 0.01 level. **Significant at 0.05 level. *Significant at 0.1 level.

the technology stock and physical capital stock separately. Model 1 in Table 5 presents estimates of the coefficient on the stock of intellectual property products. The coefficient estimates are highest among electrical products manufacturing, motor vehicles manufacturing and machinery manufacturing. These three sectors are also the ones that invest most intensively on technologies.[5] Model 2 includes interaction terms with physical capital: the coefficient estimates are the largest among the same three sectors. On the other hand, retail and transportation industries have negative though insignificant coefficient estimates, suggesting capital-skill substitutability. This finding indicates that the skill-biased technology changes and capital-skill complementarity are most obvious in capital-intensive sectors, whereas sectors that hold low stock of physical capital exhibit potential capital-skill substitutability.

Summing up, disparities remain in the relationships between capital and skill in different sectors. On one hand, capital-intensive sectors (e.g., electric products manufacturing) show strong evidence in favor of SBTC and capital-skill complementarity. On the other hand, sectors that hold low stock of physical capital (e.g., transportation) exhibit potential capital-skill substitutability.

VII. Conclusion

My results show robust evidence of capital-skill and technology-skill complementarities across the 18 sectors analyzed. The complementary relationship is becoming stronger across decades and is strongest in the 21st century. Contrary to some claims that suggest the possibility of smart machines replacing high-skilled labor, my econometric analysis of the wage share ratio over last 40 years indicates a continued trend for technological changes to favor, and complement with skilled labor. Disparities remain in the magnitude of the capitals effect on skilled labors wage share for different industries. When examining the coefficients separately for each sector, all of them exhibit technology-skill complementarity and most of them exhibit capital-skill complementarity. The complementary relationship is strongest for capital-intensive sectors such as electrical products manufacturing, motor vehicles manufacturing, and machinery manufacturing. On the other hand, less capital-intensive sectors such as retail and transportation suggest capital-skill substitutability.

However, the positive and significant covariance between capital and technology stock wage share is rather mechanical than causal. My finding reveals that whatever factors that cause industry-level technology and capital stock to increase in the past 40 years also lead to an increase in the skill labors wage share. The models are subject to potential endogenous bias as it is possible that increased supply, rather than demand, of highly skilled labor motivates companies to invest more in technology-embodied capital. For future studies instrumental variables uncorrelated with the wage share ratio (such as government spending on R&D) could

[5] See the Appendix for a plot of the technology intensity across industries.

Table 5: Changes in the Skilled Labor's Wage Share, by Industries

Model	1	2
ln(IPP/Y)		0.0634***
		(0.0077)
ln(K/Y)	0.0342**	
	(0.0141)	
ln(Y)	0.0049	0.0634***
	(0.0191)	(0.0077)
Finance	0.1060***	0.0787***
	(0.0164)	(0.0151)
Apparel	0.0744***	0.0238
	(0.0129)	(0.0234)
Chemical Products	0.0642***	0.0487**
	(0.0100)	(0.0207)
Electrical Products	0.3040***	0.1880***
	(0.0246)	(0.0167)
Food	0.1020***	0.0871***
	(0.0148)	(0.0173)
Furniture	0.0328**	0.0036
	(0.0138)	(0.0156)
Machinery	0.1260***	0.0977***
	(0.0166)	(0.0173)
Metal	0.0397**	0.0264
	(0.0200)	(0.0215)
Motor Vehicles	0.1350***	0.1090***
	(0.0215)	(0.0144)
Nonmetallic Products	0.0631***	0.0551***
	(0.0204)	(0.0185)
Paper	0.1260***	0.0957***
	(0.0114)	(0.0216)
Printing	0.0811***	0.0621***
	(0.0102)	(0.0196)
Rubber	0.0687***	0.0445***
	(0.0219)	(0.0159)
Textile Mills	0.0732***	0.0246
	(0.0114)	(0.0281)
Wood	0.0371***	0.0027
	(0.0118)	(0.0241)
Retail	0.0178**	-0.0183
	(0.0077)	(0.0200)
Transportation	0.0238***	-0.0061
	(0.0076)	(0.0239)
Wholesale	0.0391***	0.0144
	(0.0084)	(0.0236)
Constant	1.2010***	1.2940***
	(0.2070)	(0.1430)
Adjusted R Squared	0.89	0.90
No. of Observations	738	738

Note: T-statistics in parentheses (z-statistics for random effects model). ***Significant at 0.01 level. **Significant at 0.05 level. *Significant at 0.1 level.

be used to correct the endogeneity bias.

Another potential area for future studies is to redefine skilled labor not based on education levels but on occupational tasks performed at work. Autor et al. (2003) introduce a new methodology for analyzing changes in the skill demands: instead of using average educational levels of workers as a proxy for skill demands, they draw a distinction between skills and tasks, and argue that advances in technologies first change the labor division between workers and machines, then task composition, and finally the demand for different skills. Using data on task requirements from the Dictionary of Occupational Titles (DOT) and the Census and Current Population Survey, the authors form a panel dataset of occupational task inputs from 1960 to 1998. They find a consistent increase in the demand for non-routine cognitive tasks (e.g., consulting, marketing, engineering), and non-routine manual tasks (e.g., driving cabs, cleaning buildings), and a decrease in routine cognitive and manual tasks (e.g., clerical and bookkeeping jobs). They argue that the information and communication technologies function through predefined rules and algorithms, and therefore substitute programmable routine tasks and complements non-routine tasks that are beyond present programming capacities. Because occupational datasets are not available for years after 2005, the framework can not be tested over a longer horizon. In the future, it remains of interest to examine the effect of new technologies on task composition and skill demand.

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Appendix

A. Crosswalk between the CPS and the BEA

The table below demonstrates how I map industries between the CPS and the BEA datasets. The CPS dataset uses a three-digit coding system to store industry information in the ind1990 variable. The BEA uses North American Industry Classification System (NAICS) and aggregates industry information to the two-digit level.

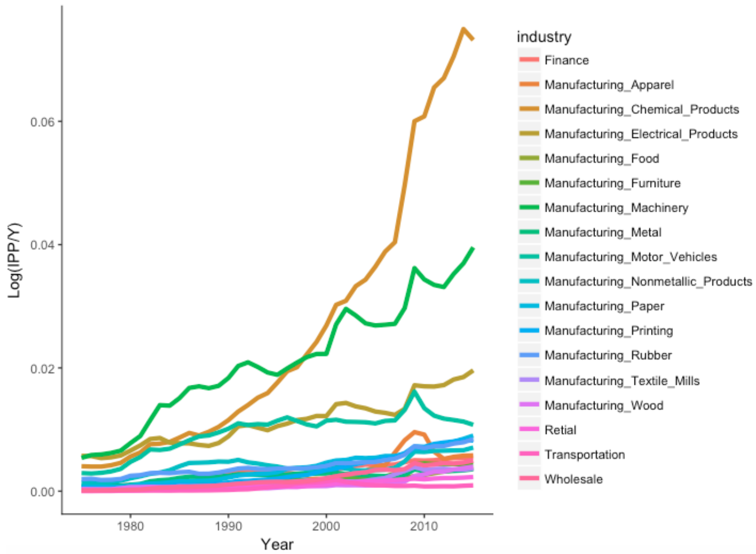
Industry		CPS (ind1990)	BEA (Line Number)
Wholesale trade		500 ~ 571	33
Retail		580 ~ 691	34
Transportation		400 ~ 432	35
Finance		700 ~ 711	49
Manufacturing Durable	Wood	230 ~ 241	13
	Furniture	242	22
	Nonmetallic Products	250 ~ 262	14
	Metal	270 ~ 301	15 ~ 16
	Machinery	310 ~ 332	17 ~ 18
	Electrical Products	340 ~ 350	19
	Motor Vehicles	351 ~ 370	20 ~21
Manufacturing Nondurable	Food	110 ~ 130	25
	Textile Mills	132 ~ 150	26
	Apparel	151 ~ 152, 220 ~ 222	27
	Paper	160 ~ 162	28
	Printing	171 ~ 172	29
	Chemical Products	180 ~ 192	31
	Rubber	210 ~ 212	32

B. Summary Statistics

The table below is a statistical summary of the variables employed in the paper.

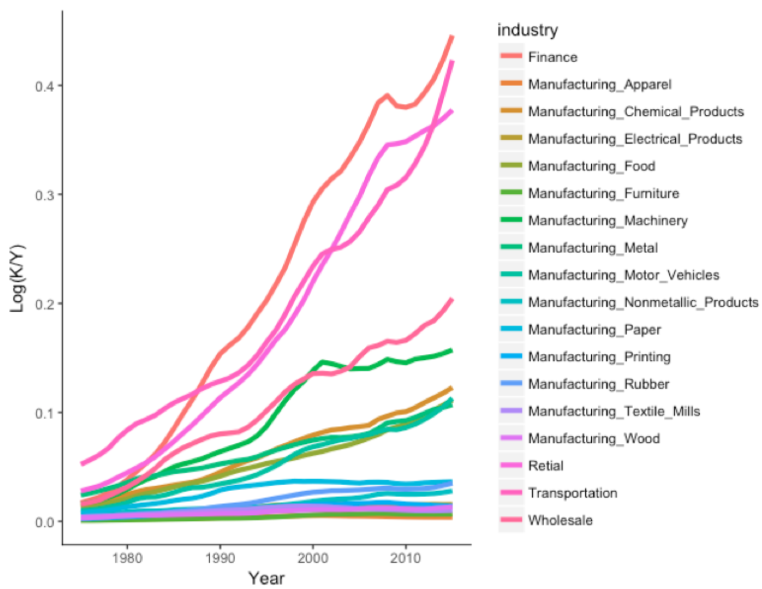
Variable	Obs	Mean	Std. Dev.	Min	Max
year	738	1995	11.84018	1975	2015
ind_code	738	11.55556	5.286914	3	21
wage_share	738	0.2929382	0.14608	0.0601058	0.7102382
employment_share	738	0.1894989	0.1067678	0.016667	0.562397
ln(IPP/Y)	738	-6.008655	1.338385	-10.80983	-2.590687
ln(K/Y)	738	-3.601081	1.364823	-7.118826	-0.8078704
ln(Y)	738	7.816067	1.049408	5.178351	9.897736

C. Technology Intensity



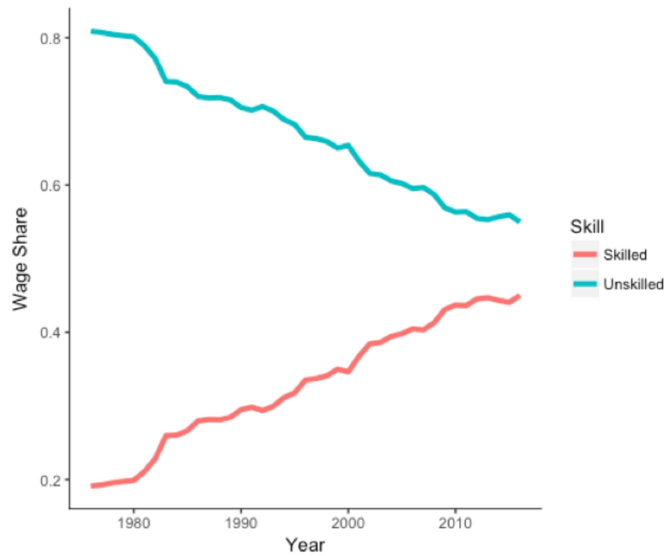
The figure above plots the log of the output adjusted intellectual property product stocks for each industry. The most technology-intensive industries are chemical products manufacturing, electrical products manufacturing, motor vehicles manufacturing and machinery manufacturing. The least intensive ones are wood manufacturing, retail and transportation.

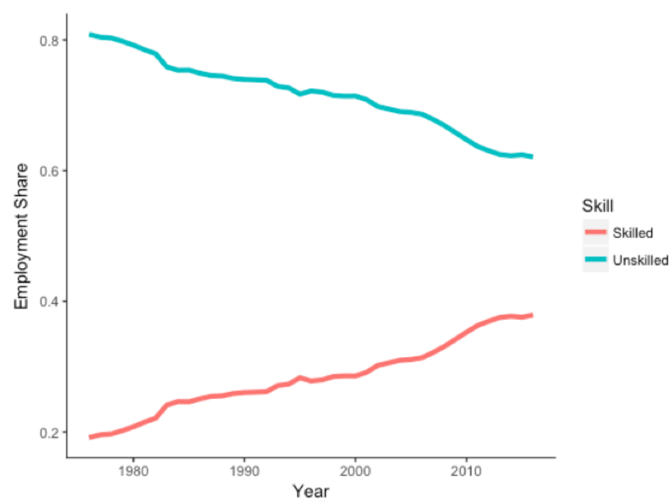
D. Capital Intensity



The figure above plots the log of the output adjusted physical capital stocks for each industry. The most capital-intensive industries are finance, retail and transportation. The least intensive ones are furniture and apparel sectors.

E. Aggregate Wage Share and Employment Share





The two figures above plot two different measures of the independent variables used in the paper: the wage share and the employment share ratio. From 1975 to 2015, skilled labor is progressively taking up a larger percent share of total wage bill and employment.