Is a College Education Still Enough? The IT-Labor Relationship with Education Level, Task Routineness, and Artificial Intelligence

Online Appendix

Appendix A: Summary of Literature on SBTC and RBTC

Categories	Studies	Methods	Time Periods	Data Sources	Measures of IT	Measures of Labor	Key Findings	IT vs. Labor
SBTC	Bartel and Lichtenberg (1987)	Regression analysis	1960, 1970, and 1980	Bureau of Industrial Economics' Capital of Stocks Data Base	Experience of technology	Total labor cost	Firms introducing new technologies hire more skilled workers, although demand for educated workers declines as workers gain more experience with the technologies.	Complements when technologies are new; substitutes as capital age increases
	Bound and Johnson (1992)	Regression analysis	1973-1979 and 1979-1988	Current Population Survey	Proportion of workers employed in industries where growth of efficiency differs from the industry-average growth rate	Aggregate employment and demographic group	Technical change is complementary to skilled workers and is the primary cause for the increase in wage difference between college-educated and non-college educated workers	Complements for college-educated labor
	Krueger (1993)	Regression analysis	1984-1989	Current Population Survey	Whether a worker uses a computer at work	Labor hours	Use of computers at work is associated with higher wages	Complements for educated labor with computer training
	Autor et al. (1998)	Correlational analysis	1940-1996	Current Population Survey	Fraction of workers who directly use a computer keyboard	Labor hours	Persistent growth in relative demand for college graduates, which is correlated with increased use of computers among the	Complements for skilled labor

							industries	
SBTC	Acemoglu (1998)	Analytical models	N/A	N/A	N/A	N/A	More skilled workers would increase the market for technologies, and hence new technologies will be complementary to skills	Complements for skilled labor
	Goldin and Katz (1998)	Regression analysis	1909-1940	Census of Manufactures, NBER Manufacturing Productivity Database	1) Time dummy to capture cross-industry tech trends; 2) The change in the percentage of horsepower run by purchased electricity	Total labor cost	Both capital and technology are complements with skilled labor	Complements for skilled or educated labor
	Bresnahan (1999)	Theory development (qualitative)	N/A	N/A	N/A	N/A	Technical changes in the organizations automate moderate-skill, white-collar work while increasing the demand for highly skilled professionals	Substitutes for moderate-skill labor; complements for highly skilled labor
	Acemoglu (2002)	Literature survey; regression analysis	Prior to 2002	N/A	N/A	N/A	Evidence for acceleration in skill bias when there is rapid technical change, which increases the skill premium for educated labor	Complements for skilled labor
	Acemoglu and Autor (2011)	Analytical model	Prior to 2011	N/A	N/A	N/A	Authors proposed a task-based model in which the assignment of skills to tasks is endogenous and technical change may involve the substitution of machines for certain tasks previously performed by labor	Depends on skill level of labor and nature of the technical change
	Autor et al.	OLS	1960-	CPS/DOT	Percentage	Inputs of	IT substitutes for workers in	Substitutes or

RBTC	(2003)		1998		of employees using computer at work	routine and nonroutine tasks	performing routine tasks while complementing workers in performing nonroutine tasks.	complements
	Autor et al. (2006)	tabulation	1980-1990	CPS	N/A	Percentage of change in employment share of jobs of different wage levels	IT complements nonroutine cognitive tasks, substitutes for routine tasks, and have little impact on nonroutine manual tasks	Labor market polarization
	Goos and Manning (2007)	OLS	1975-1999	Britain New Earnings Survey (NES) and the Labor Force Survey (LFS)	N/A	Percentage of change in employment share of jobs of different wage levels	IT leads to rising relative demand in well-paid, skilled jobs (that typically require nonroutine cognitive skills) and in low-paid, least-skilled jobs (that typically require nonroutine manual skills) and falling relative demand in the “middling” jobs that have typically required routine manual and cognitive skills	Job polarization
	Autor et al. (2008)	OLS	1963-2005	CPS	N/A	Percentage of change in employment share of jobs of different wage levels	IT complements highly educated workers engaged in abstract tasks, substitutes for moderately educated workers performing routine tasks, and has less impact on low-skilled workers performing manual tasks	Labor market polarization
	Goos et al. (2009)	OLS		European Union Labour Force Survey (ELFS) in 16 European countries	N/A	Change in employment share of jobs of different wage levels	High- and low-paying occupations expand their employment shares relative to the occupations paying close to the mean wage; job polarization is pervasive in European countries	Job routinization/ job and wage polarization
	Acemoglu	Plotting	1993-	CPS/		Employment	Two trends are identified	Job polarization

	and Autor (2011)		2005/ 1992-2008	Eurostat		share at different skill levels	across US and European countries: rapid employment growth in both high- and low-education jobs, and substantially reduced share of employment accounted for by “middle skill” jobs	
	Autor and Dorn (2013)	OLS	1980-2005	American Community Survey (ACS)	N/A	Number of computers per employee	Industries with more routine tasks experience greater adoption of IT, coinciding with the displacement of labor from routine tasks; low-skill workers relocate from routine, task-intensive occupations to service occupations; wages increase for both high-skill, abstract and low-skill, manual labor; skill upgrade for labor, driven by complementarity between computer capital and high-skill labor	Polarization of labor market and earnings
RBTC	Goos et al. (2014)	tabulation	1993-2010	European Union Labour Force Survey (ELFS)	N/A	Employment share of jobs at different wage levels	The employment structure in Western Europe has been polarizing, with rising employment shares for high-paid professionals and managers as well as low-paid, personal service workers and falling employment shares of manufacturing and routine office workers	Labor force polarization
	Michaels et al. (2014)	OLS	1980-2004	EUKLEMS data from 11 countries	ICT capital	Wages for labor of different skill levels	Industries where ICT grew most strongly were those with the largest shifts toward the most skilled and the largest shifts away from the middle skilled, with the	Polarization of labor market and earnings

							least skilled largely unaffected	

Appendix B: Math Proof for Table 3 in the Paper

Let *i* and *j* be the quantities of inputs for factors *i* and *j*, and P_j be the price of factor *j*, and Q_j be the quantity input of factor *j*. Symbol ↑ represents increase and ↓ decrease.

If $\mathrm{AES_{ij}} > 0$: $\mathrm{P_j} \uparrow \Rightarrow \mathrm{Q_j} \downarrow \textit{and } \mathrm{Q_i} \uparrow$ (1)

Conclusion: input *j* is a substitute for input *i* regardless of MES. Mathematically, $\mathrm{MES_{ij}}$ can only be positive in this case; otherwise, it would conflict with (1).

If $\mathrm{AES_{ij}} < 0$: $\mathrm{P_j} \uparrow \Rightarrow \mathrm{Q_j} \downarrow \textit{and } \mathrm{Q_i} \downarrow$

If $\mathrm{MES_{ij}} > 0, \mathrm{P_j} \uparrow \Rightarrow \mathrm{Q_j} \downarrow \textit{ and } \Delta \mathrm{Q_i}/\Delta \mathrm{Q_j} \uparrow \Rightarrow |\Delta \mathrm{Q_i}\%| < |\Delta \mathrm{Q_j}\%|$

Conclusion: input *j* is a weak complement for input *i*.

If $\mathrm{MES_{ij}} < 0, \mathrm{P_j} \uparrow \Rightarrow \mathrm{Q_j} \downarrow \textit{ and } \Delta \mathrm{Q_i}/\Delta \mathrm{Q_j} \uparrow \Rightarrow |\Delta \mathrm{Q_i}\%| > |\Delta \mathrm{Q_j}\%|$

Conclusion: input *j* is a strong complement for input *i*.

Appendix C: Steps for Estimating AES and MES from the Translog Function

Step 1: AES for a general production function with three input factors

For a production function with three input factors, $V = f(C, K, L)$, the output elasticities of the inputs are given as:

1) $\eta_C = \partial \log V / \partial \log C$
2) $\eta_K = \partial \log V / \partial \log K$
3) $\eta_L = \partial \log V / \partial \log L$

For simplicity, we drop the industry and time subscripts of the variables. The marginal products are given as:

1) $f_C = \partial V / \partial C = \eta_C \cdot (V / C)$
2) $f_K = \partial V / \partial K = \eta_K \cdot (V / K)$
3) $f_L = \partial V / \partial L = \eta_L \cdot (V / L)$

The **Allen Elasticity of Substitution (AES)** between *C* and *K* is:

$$\sigma_{CK}^{A} = \frac{Cf_C + Kf_K + Lf_L}{CK} \cdot \frac{H_{CK}}{H}$$

where H is the determinant of the bordered Hessian: $H = \begin{vmatrix} 0 & f_C & f_K & f_L \\ f_C & f_{CC} & f_{CK} & f_{CL} \\ f_K & f_{KC} & f_{KK} & f_{KL} \\ f_L & f_{LC} & f_{LK} & f_{LL} \end{vmatrix}$

and H_{CK} is the cofactor associated with f_{CK} in H, i.e.: $H_{CK} = -\begin{vmatrix} 0 & f_C & f_L \\ f_K & f_{KC} & f_{KL} \\ f_L & f_{LC} & f_{LL} \end{vmatrix}$

Similarly: $\sigma_{CL}^{A} = \frac{Cf_C + Kf_K + Lf_L}{CL} \cdot \frac{H_{CL}}{H}$, and $H_{CL} = \begin{vmatrix} 0 & f_C & f_K \\ f_K & f_{KC} & f_{KK} \\ f_L & f_{LC} & f_{LK} \end{vmatrix}$

and $\sigma_{KL}^{A} = \frac{Cf_C + Kf_K + Lf_L}{KL} \cdot \frac{H_{KL}}{H}$, and $H_{KL} = -\begin{vmatrix} 0 & f_C & f_K \\ f_C & f_{CC} & f_{CK} \\ f_L & f_{LC} & f_{LL} \end{vmatrix}$

Step 2: AES for the Translog function with three input factors

Now if we apply the above to the Translog function:

$$\begin{aligned} \log(V) &= \delta + \alpha_C \log C + \alpha_K \log K + \alpha_L \log L \\ &+ \beta_{CC}(\log C)^2 + \beta_{KK}(\log K)^2 + \beta_{LL}(\log L)^2 \\ &+ \beta_{CK} \log C \log K + \beta_{CL} \log C \log L + \beta_{KL} \log K \log L + \varepsilon \end{aligned}$$

We have:

1) $\eta_C = \partial \log V / \partial \log C = \alpha_C + 2\beta_{CC} \log C + \beta_{CK} \log K + \beta_{CL} \log L$
2) $\eta_K = \partial \log V / \partial \log K = \alpha_K + 2\beta_{KK} \log K + \beta_{CK} \log C + \beta_{KL} \log L$
3) $\eta_L = \partial \log V / \partial \log L = \alpha_L + 2\beta_{LL} \log L + \beta_{CL} \log C + \beta_{KL} \log K$

The marginal products are:

1) $f_C = \eta_C \cdot (V / C)$
2) $f_K = \eta_K \cdot (V / K)$
3) $f_L = \eta_L \cdot (V / L)$

The second derivatives are:

1) $f_{CC} = \frac{V}{C} \frac{2\beta_{CC}}{C} + \eta_C \frac{f_C C - V}{C^2} = \frac{2\beta_{CC} V}{C^2} + \frac{f_C^{\ 2}}{V} - \frac{f_C}{C}$,

$f_{CK} = \frac{V}{C} \cdot \frac{\beta_{CK}}{K} + \eta_C \frac{f_K}{C} = \frac{V\beta_{CK}}{CK} + \frac{f_C f_K}{V}$, and

$f_{CL} = \frac{V}{C} \cdot \frac{\beta_{CL}}{L} + \eta_C \frac{f_L}{C} = \frac{V\beta_{CL}}{CL} + \frac{f_C f_L}{V}$

2) $f_{KC} = \frac{V}{K} \cdot \frac{\beta_{CK}}{C} + \eta_K \frac{f_C K}{C^2} = \frac{V\beta_{CK}}{KC} + \frac{f_K f_C}{V}$,

$f_{KK} = \frac{V}{K} \cdot \frac{2\beta_{KK}}{K} + \eta_K \frac{f_K K - V}{K^2} = \frac{2\beta_{KK} V}{K^2} + \frac{f_K^{\ 2}}{V} - \frac{f_K}{K}$, and

$f_{KL} = \frac{V}{K} \cdot \frac{\beta_{KL}}{L} + \eta_K \frac{f_L K}{K^2} = \frac{V\beta_{KL}}{KL} + \frac{f_K f_L}{V}$

3) $f_{LC} = \frac{V}{L} \cdot \frac{\beta_{CL}}{C} + \eta_L \frac{f_C L}{L^2} = \frac{V\beta_{CL}}{LC} + \frac{f_L f_C}{V}$,

$$f_{LK} = \frac{V}{L}\cdot\frac{\beta_{KL}}{K} + \eta_L \frac{f_K L}{L^2} = \frac{V\beta_{KL}}{LK} + \frac{f_L f_K}{V}, \text{ and}$$

$$f_{LL} = \frac{V}{L}\cdot\frac{2\beta_{LL}}{L} - \eta_L \frac{f_L L - V}{L^2} = \frac{2\beta_{LL}V}{L^2} + \frac{f_L{}^2}{V} - \frac{f_L}{L}$$

(note: $f_{ij} = f_{ji}$)

and then, H , H_{CK}, H_{CL}, H_{KL} , σ^A_{CK} , σ^A_{CL}, and σ^A_{KL} can all be calculated accordingly.

Step 3: MES for a general production function with three input factors

The **Morishima elasticity of substitution (MES)** of the three factor inputs are:

$$\sigma^M_{CK} = \frac{f_K K}{f_C C + f_K K + f_L L}\cdot(\sigma^A_{CK} - \sigma^A_{KK}),$$

$$\sigma^M_{CL} = \frac{f_L L}{f_C C + f_K K + f_L L}\cdot(\sigma^A_{CL} - \sigma^A_{LL}), \text{ and}$$

$$\sigma^M_{KL} = \frac{f_L L}{f_C C + f_K K + f_L L}\cdot(\sigma^A_{KL} - \sigma^A_{LL})$$

Step 4: AES for the Translog function with five input factors

The five-factor Tanslog function proceeds in a similar manner:

$$\begin{aligned} \log(V) = {} & \delta + \alpha_C \log C + \alpha_K \log K + \alpha_{Lh} \log Lh + \alpha_{Lm} \log Lm + \alpha_{Ll} \log Ll \\ & + \beta_{CC}(\log C)^2 + \beta_{KK}(\log K)^2 + \beta_{LhLh}(\log Lh)^2 + \beta_{LmLm}(\log Lm)^2 + \beta_{LlLl}(\log Ll)^2 \\ & + \beta_{CK}\log C\log K + \beta_{CLh}\log C\log Lh + \beta_{CLm}\log C\log Lm + \beta_{CLl}\log C\log Ll \\ & + \beta_{KLh}\log K\log Lh + \beta_{KLm}\log K\log Lm + \beta_{KLl}\log K\log Ll \\ & + \beta_{LhLm}\log Lh\log Lm + \beta_{LhLl}\log Lh\log Ll + \beta_{LmLl}\log Lm\log Ll + \varepsilon \end{aligned} \quad (2)$$

We have:

1) $\eta_C = \partial\log V / \partial\log C = \alpha_C + 2\beta_{CC}\log C + \beta_{CK}\log K + \beta_{CLh}\log Lh + \beta_{CLm}\log Lm + \beta_{CLl}\log Ll$

2) $\eta_K = \partial\log V / \partial\log K = \alpha_K + 2\beta_{KK}\log K + \beta_{CK}\log C + \beta_{KLh}\log Lh + \beta_{KLm}\log Lm + \beta_{KLl}\log Ll$

3) $\eta_{Lh} = \partial\log V / \partial\log Lh = \alpha_{Lh} + 2\beta_{LhLh}\log Lh + \beta_{CLh}\log C + \beta_{KLh}\log K + \beta_{LhLm}\log Lm + \beta_{LhLl}\log Ll$

4) $\eta_{Lm} = \partial\log V / \partial\log Lm = \alpha_{Lm} + 2\beta_{LmLm}\log Lm + \beta_{CLm}\log C + \beta_{KLm}\log K + \beta_{LhLm}\log Lh + \beta_{LmLl}\log Ll$

5) $\eta_{Ll} = \partial\log V / \partial\log Ll = \alpha_{Ll} + 2\beta_{LlLl}\log Ll + \beta_{CLl}\log C + \beta_{KLl}\log K + \beta_{LhLl}\log Lh + \beta_{LmLl}\log Lm$

The marginal products are:

1) $f_C = \eta_C\cdot(V/C)$
2) $f_K = \eta_K\cdot(V/K)$
3) $f_{Lh} = \eta_{Lh}\cdot(V/Lh)$
4) $f_{Lm} = \eta_{Lm}\cdot(V/Lm)$

5) $f_{Ll} = \eta_{Ll} \cdot (V / Ll)$

The second derivatives are:

1) $f_{CC} = \frac{2\beta_{CC}V}{C^2} + \frac{f_C{}^2}{V} - \frac{f_C}{C}$, $f_{CK} = \frac{V\beta_{CK}}{CK} + \frac{f_C f_K}{V}$, $f_{CLh} = \frac{V\beta_{CLh}}{CLh} + \frac{f_C f_{Lh}}{V}$,
$f_{CLm} = \frac{V\beta_{CLm}}{CLm} + \frac{f_C f_{Lm}}{V}$, and $f_{CLl} = \frac{V\beta_{CLl}}{CLl} + \frac{f_C f_{Ll}}{V}$

2) $f_{KC} = \frac{V\beta_{CK}}{KC} + \frac{f_K f_C}{V}$, $f_{KK} = \frac{2\beta_{KK}V}{K^2} + \frac{f_K{}^2}{V} - \frac{f_K}{K}$, $f_{KLh} = \frac{V\beta_{KLh}}{KLh} + \frac{f_K f_{Lh}}{V}$,
$f_{KLm} = \frac{V\beta_{KLm}}{KLm} + \frac{f_K f_{Lm}}{V}$, and $f_{KLl} = \frac{V\beta_{KLl}}{KLl} + \frac{f_K f_{Ll}}{V}$

3) $f_{LhC} = \frac{V\beta_{CLh}}{LhC} + \frac{f_{Lh} f_C}{V}$, $f_{LhK} = \frac{V\beta_{KLh}}{LhK} + \frac{f_{Lh} f_K}{V}$, $f_{LhLh} = \frac{2\beta_{LhLh}V}{Lh^2} + \frac{f_{Lh}{}^2}{V} - \frac{f_{Lh}}{Lh}$,
$f_{LhLm} = \frac{V\beta_{LmLh}}{LhLm} + \frac{f_{Lh} f_{Lm}}{V}$, and $f_{LhLl} = \frac{V\beta_{LlLh}}{LhLl} + \frac{f_{Lh} f_{Ll}}{V}$

4) $f_{LmC} = \frac{V\beta_{CLm}}{LmC} + \frac{f_{Lm} f_C}{V}$, $f_{LmK} = \frac{V\beta_{KLm}}{LmK} + \frac{f_{Lm} f_K}{V}$, $f_{LmLh} = \frac{V\beta_{LmLh}}{LhLm} + \frac{f_{Lh} f_{Lm}}{V}$
$f_{LmLm} = \frac{2\beta_{LmLm}V}{Lm^2} + \frac{f_{Lm}{}^2}{V} - \frac{f_{Lm}}{Lm}$, , and $f_{LmLl} = \frac{V\beta_{LmLl}}{LmLl} + \frac{f_{Lm} f_{Ll}}{V}$

5) $f_{LlLl} = \frac{2\beta_{LlLl}V}{Ll^2} + \frac{f_{Ll}{}^2}{V} - \frac{f_{Ll}}{Ll}$

(note: $f_{ij} = f_{ji}$)

The AES between C and K is:

$$\sigma_{CK}^{A} = \frac{\sum(x_i f_i)}{CK} \cdot \frac{H_{CK}}{H},$$

where $\sum(x_i f_i) = Cf_C + Kf_K + Lhf_{Lh} + Lmf_{Lm} + Llf_{Ll}$, H is the determinant of the bordered Hessian:

$$H = \begin{vmatrix} 0 & f_C & f_K & f_{Lh} & f_{Lm} & f_{Ll} \\ f_C & f_{CC} & f_{CK} & f_{CLh} & f_{CLm} & f_{CLl} \\ f_K & f_{KC} & f_{KK} & f_{KLh} & f_{KLm} & f_{KLl} \\ f_{Lh} & f_{LhC} & f_{LhK} & f_{LhLh} & f_{LhLm} & f_{LhLl} \\ f_{Lm} & f_{LmC} & f_{LmK} & f_{LmLh} & f_{LmLm} & f_{LmLl} \\ f_{Ll} & f_{LlC} & f_{LlK} & f_{LlLh} & f_{LlLm} & f_{LlLl} \end{vmatrix}$$

and H_{CK} is the cofactor associated with f_{CK} in H, i.e.:

$$H_{CK} = -\begin{vmatrix} 0 & f_C & f_{Lh} & f_{Lm} & f_{Ll} \\ f_K & f_{KC} & f_{KLh} & f_{KLm} & f_{KLl} \\ f_{Lh} & f_{LhC} & f_{LhLh} & f_{LhLm} & f_{LhLl} \\ f_{Lm} & f_{LmC} & f_{LmLh} & f_{LmLm} & f_{LmLl} \\ f_{Ll} & f_{LlC} & f_{LlLh} & f_{LlLm} & f_{LlLl} \end{vmatrix}$$

Similarly:

$$\sigma_{CLh}^{A}=\frac{\sum(x_i f_i)}{C\cdot Lh}\cdot\frac{H_{CLh}}{H}\text{, and } H_{CLh}=\begin{vmatrix} 0 & f_C & f_K & f_{Lm} & f_{Ll} \\ f_K & f_{KC} & f_{KK} & f_{KLm} & f_{KLl} \\ f_{Lh} & f_{LhC} & f_{LhK} & f_{LhLm} & f_{LhLl} \\ f_{Lm} & f_{LmC} & f_{LmK} & f_{LmLm} & f_{LmLl} \\ f_{Ll} & f_{LlC} & f_{LlK} & f_{LlLm} & f_{LlLl} \end{vmatrix}$$

$$\sigma_{CLm}^{A}=\frac{\sum(x_i f_i)}{C\cdot Lm}\cdot\frac{H_{CLm}}{H}\text{, and } H_{CLm}=-\begin{vmatrix} 0 & f_C & f_K & f_{Lh} & f_{Ll} \\ f_K & f_{KC} & f_{KK} & f_{KLh} & f_{KLl} \\ f_{Lh} & f_{LhC} & f_{LhK} & f_{LhLh} & f_{LhLl} \\ f_{Lm} & f_{LmC} & f_{LmK} & f_{LmLh} & f_{LmLl} \\ f_{Ll} & f_{LlC} & f_{LlK} & f_{LlLh} & f_{LlLl} \end{vmatrix}$$

$$\sigma_{CLl}^{A}=\frac{\sum(x_i f_i)}{C\cdot Ll}\cdot\frac{H_{CLl}}{H}\text{, and } H_{CLl}=\begin{vmatrix} 0 & f_C & f_K & f_{Lh} & f_{Lm} \\ f_K & f_{KC} & f_{KK} & f_{KLh} & f_{KLm} \\ f_{Lh} & f_{LhC} & f_{LhK} & f_{LhLh} & f_{LhLm} \\ f_{Lm} & f_{LmC} & f_{LmK} & f_{LmLh} & f_{LmLm} \\ f_{Ll} & f_{LlC} & f_{LlK} & f_{LlLh} & f_{LlLm} \end{vmatrix}$$

<u>Step 5: MES for the Translog function with five input factors</u>

The MES between *C*, *K*, and three levels of *L* are:

$$\sigma_{CK}^{M}=\frac{f_K K}{f_C C+f_K K+f_{Lh}Lh+f_{Lm}Lm+f_{Ll}Ll}\cdot(\sigma_{CK}^{A}-\sigma_{KK}^{A}),$$

$$\sigma_{CLh}^{M}=\frac{f_{Lh} Lh}{f_C C+f_K K+f_{Lh}Lh+f_{Lm}Lm+f_{Ll}Ll}\cdot(\sigma_{CLh}^{A}-\sigma_{LhLh}^{A}),$$

$$\sigma_{CLm}^{M}=\frac{f_{Lm} Lm}{f_C C+f_K K+f_{Lh}Lh+f_{Lm}Lm+f_{Ll}Ll}\cdot(\sigma_{CLm}^{A}-\sigma_{LmLm}^{A})\text{, and}$$

$$\sigma_{CLl}^{M}=\frac{f_{Lh} Ll}{f_C C+f_K K+f_{Lh}Lh+f_{Lm}Lm+f_{Ll}Ll}\cdot(\sigma_{CLl}^{A}-\sigma_{LlLl}^{A})$$

Appendix D: Three-Digit NAICS Industry Descriptions

(yellow)	High AIE
(green)	High STEM
(blue)	Nonroutine

2007	NAICS Code		Industry Title
111CA	111CA	111CA	Farms
113FF	113FF	113FF	Forestry, fishing, and related activities
211	211	211	Oil and gas extraction
212	212	212	Mining, except oil and gas
213	213	213	Support activities for mining
22	22	22	Utilities
23	23	23	Construction
311FT	311FT	311FT	Food and beverage and tobacco products
315AL	315AL	315AL	Apparel and leather and allied products
321	321	321	Wood products
322	322	322	Paper products
323	323	323	Printing and related support activities
324	324	324	Petroleum and coal products
325	325	325	Chemical products
326	326	326	Plastics and rubber products
327	327	327	Nonmetallic mineral products
331	331	331	Primary metals
332	332	332	Fabricated metal products
333	333	333	Machinery
334	334	334	Computer and electronic products
335	335	335	Electrical equipment, appliances, and components
3361MV	3361MV	3361MV	Motor vehicles, bodies and trailers, and parts
3364OT	3364OT	3364OT	Other transportation equipment
337	337	337	Furniture and related products
339	339	339	Miscellaneous manufacturing
42	42	42	Wholesale trade
44RT	44RT	44RT	Retail trade
481	481	481	Air transportation
482	482	482	Rail transportation
483	483	483	Water transportation
484	484	484	Truck transportation
485	485	485	Transit and ground passenger transportation
486	486	486	Pipeline transportation
487OS	487OS	487OS	Other transportation and support activities
493	493	493	Warehousing and storage

511	511	511	Publishing industries, except internet (includes software)
512	512	512	Motion picture and sound recording industries
513	513	513	Broadcasting and telecommunications
514	514	514	Data processing, internet publishing, and other information services
521CI	521CI	521CI	Federal Reserve banks, credit intermediation, and related activities
523	523	523	Securities, commodity contracts, and investments
524	524	524	Insurance carriers and related activities
531	531	531	Real Estate
532RL	532RL	532RL	Rental and leasing services and lessors of intangible assets
5411	5411	5411	Legal services
5412OP	5412OP	5412OP	Miscellaneous professional, scientific, and technical services
5415	5415	5415	Computer systems design and related services
55	55	55	Management of companies and enterprises
561	561	561	Administrative and support services
562	562	562	Waste management and remediation services
61	61	61	Educational services
621	621	621	Ambulatory health care services
622	622	622	Hospitals
623	623	623	Nursing and residential care facilities
624	624	624	Social assistance
711AS	711AS	711AS	Performing arts, spectator sports, museums, and related activities
713	713	713	Amusements, gambling, and recreation industries
721	721	721	Accommodation
722	722	722	Food services and drinking places
81	81	81	Other services, except government

Appendix E: Summary Statistics

Table A1. Summary Statistics (1998-2013)

Samples	Variable	Mean	Std. dev.	Min.	Max.
Full Sample (N=952)	Value Added (V_{it})	205,987	270,856	5,511	1,865,536
	IT Capital (C_{it})	24,559	45,787	514	406,635
	Non-IT Capital (K_{it})	254,424	305,216	12,909	1,814,622
	High-education Labor (Lh_{it})	156	254	0	1,429
	Middle-education Labor (Lm_{it})	847	1,113	0	6,733
	Low-education Labor (Ll_{it})	729	1,173	0	6,773
	Average Work Experience for Lh_{it} ($edu\_hig\_exp_{it}$)	21	5	0	46
	Average Work Experience for Lm_{it} ($edu\_mid\_exp_{it}$)	22	2	0	45
	Average Work Experience for Ll_{it} ($edu\_low\_exp_{it}$)	27	2	0	33
Routine-intensive Industries (N=476)	Value Added (V_{it})	171,151	187,371	10,948	1,108,276
	IT Capital (C_{it})	26,684	58,338	630	406,635
	Non-IT Capital (K_{it})	314,231	372,348	12,908	1,814,622
	High-education Labor (Lh_{it})	136	244	0	1,429
	Middle-education Labor (Lm_{it})	842	1,294	0	6,733
	Low-education Labor (Ll_{it})	815	1,347	0	6,773
	Average Work Experience for Lh_{it} ($edu\_hig\_exp_{it}$)	20	4	0	32
	Average Work Experience for Lm_{it} ($edu\_mid\_exp_{it}$)	22	2	0	45
	Average Work Experience for Ll_{it} ($edu\_low\_exp_{it}$)	26	3	0	33
Nonroutine-intensive Industries (N=476)	Value Added (V_{it})	240,822	330,666	5,510	1,865,536
	IT Capital (C_{it})	22,433	28,013	514	157,147
	Non-IT Capital (K_{it})	194,616	201,736	13,783	1,086,064
	High-education Labor (Lh_{it})	176	263	0	1,285
	Middle-education Labor (Lm_{it})	852	898	21	3,331
	Low-education Labor	643	964	15	4,753

	(Ll_{it})				
	Average Work Experience for Lh_{it} ($edu\_hig\_exp_{it}$)	22	5	0	46
	Average Work Experience for Lm_{it} ($edu\_mid\_exp_{it}$)	22	2	15	28
	Average Work Experience for Ll_{it} ($edu\_low\_exp_{it}$)	27	3	19	33
High AI-exposure Industries (N=444)	Value Added (V_{it})	309,827	342,508	25,417	1,865,536
	IT Capital (C_{it})	44,469	60,467	808	406,635
	Non-IT Capital (K_{it})	338,540	382,982	13,783	1,814,622
	High-education Labor (Lh_{it})	266	317	3	1,429
	Middle-education Labor (Lm_{it})	1,047	924	44	3,331
	Low-education Labor (Ll_{it})	579	757	36	4,141
	Average Work Experience for Lh_{it} ($edu\_hig\_exp_{it}$)	20	3	6	46
	Average Work Experience for Lm_{it} ($edu\_mid\_exp_{it}$)	22	2	16	27
	Average Work Experience for Ll_{it} ($edu\_low\_exp_{it}$)	27	2	20	34
Low AI-exposure Industries (N=444)	Value Added (V_{it})	119,152	139,062	5,510	778,749
	IT Capital (C_{it})	6,699	8,983	514	63,026
	Non-IT Capital (K_{it})	180,017	189,658	19,256	1,083,802
	High-education Labor (Lh_{it})	65	122	0	602
	Middle-education Labor (Lm_{it})	740	1300	0	6733
	Low-education Labor (Ll_{it})	943	1511	0	6773
	Average Work Experience for Lh_{it} ($edu\_hig\_exp_{it}$)	21	5	0	43
	Average Work Experience for Lm_{it} ($edu\_mid\_exp_{it}$)	22	2	0	45
	Average Work Experience for Ll_{it} ($edu\_low\_exp_{it}$)	26	2	0	33
High-STEM Industries (N=476)	Value Added (V_{it})	181,145	196,466	5,510	1,108,276
	IT Capital (C_{it})	29,873	55,551	1,562	406,635
	Non-IT Capital (K_{it})	269,684	348,480	13,783	1,814,622
	High-education	114	201	0	1284

	Labor (Lh_{it})				
	Middle-education Labor (Lm_{it})	537	603	17	3213
	Low-education Labor (Ll_{it})	317	255	10	1196
	Average Work Experience for Lh_{it} ($edu\_hig\_exp_{it}$)	20	4	0	46
	Average Work Experience for Lm_{it} ($edu\_mid\_exp_{it}$)	22	3	16	28
	Average Work Experience for Ll_{it} ($edu\_low\_exp_{it}$)	26	3	19	34
Low-STEM Industries (N=476)	Value Added (V_{it})	230,413	326,332	20,668	1,865,536
	IT Capital (C_{it})	19,332	32,750	514	209,152
	Non-IT Capital (K_{it})	239,416	255,122	12,908	1,086,064
	High-education Labor (Lh_{it})	196	292	0	1429
	Middle-education Labor (Lm_{it})	1152	1383	0	6733
	Low-education Labor (Ll_{it})	1134	1529	0	6773
	Average Work Experience for Lh_{it} ($edu\_hig\_exp_{it}$)	21	4	0	42
	Average Work Experience for Lm_{it} ($edu\_mid\_exp_{it}$)	22	2	0	45
	Average Work Experience for Ll_{it} ($edu\_low\_exp_{it}$)	26	3	0	32

Notes: Labor variables are in thousands of full-time equivalent employees. V_{it}, C_{it}, and K_{it} are in millions of 2009 dollars, and average work experience is measured in number of years.

Appendix F: Coefficient Estimates for Regressions

Table A2. Estimated Coefficients from the Production Functions (Full Sample)

Independent Variables	**Cobb-Douglas FGLS**	**Translog Equation (3) FGLS**	**Translog Equation (4) FGLS**	**Translog Equation (4) GMM**
α_C	0.201*** (0.017)	0.510*** (0.143)	0.573*** (0.114)	2.504*** (0.865)
α_K	0.307*** (0.021)	0.392*** (0.123)	−0.924 (0.655)	0.909 (1.008)
α_L	0.399*** (0.018)	2.327*** (0.207)		

α_{Lh}			0.398*** (0.086)	4.210*** (1.384)
α_{Lm}			0.317* (0.172)	0.503*** (0.047)
α_{Ll}			0.166** (0.078)	7.610*** (2.666)
β_{CC}		0.028*** (0.007)	0.016** (0.006)	0.167 (0.102)
β_{CK}		−0.055*** (0.015)	−0.073*** (0.013)	−0.280** (0.118)
β_{CL}		−0.037*** (0.013)		
β_{CLh}			−0.010 (0.008)	0.3105 (0.196)
β_{CLm}			0.023 (0.016)	−1.277* (0.699)
β_{CLl}			0.005* (0.002)	0.783** (0.394)
β_{KK}		0.048*** (0.009)	0.086*** (0.009)	0.081* (0.042)
β_{KL}		−0.106*** (0.017)		
β_{KLh}			−0.002 (0.008)	0.060 (0.180)
β_{KLm}			−0.025 (0.018)	0.397 (0.326)
β_{KLl}			0.006 (0.008)	-0.447 (0.472)
β_{LL}		−0.013 (0.009)		
β_{LhLh}			0.031*** (0.006)	0.411* (0.246)
β_{LhLm}			−0.027 (0.025)	−2.664 (1.971)
β_{LhLl}			−0.049*** (0.013)	0.965 (0.627)
β_{LmLm}			0.029 (0.027)	0.243 (0.190)
β_{LmLl}			−0.031 (0.026)	−3.800 (2.927)
β_{LlLl}			0.022*** (0.007)	0.890** (0.397)
N	894	882	882	814

Notes: ***p<0.01, **p<0.05, *p<0.1. Industry and year dummies as well as average work experience for the three education levels are suppressed for brevity. Standard errors are in parentheses. Numbers of observations differ slightly in columns (3) – (5) due to missing values in the three education levels (logarithmic) and the lagged independent variables.

Table A3. Estimated AES and MES (3 Factors) – Full Sample

Input *i*	Input *j*	AES_*ij*	MES_*ij*	Interpretation
C	*L*	0.958*** (0.021)	1.201*** (0.010)	Substitutes
L	*C*	0.958*** (0.021)	1.781*** (0.031)	Substitutes

Notes: Bootstrapped standard errors are in parentheses.
***p<0.01, **p<0.05, *p<0.1.

Table A4. Estimated Coefficients for Routine- vs. Nonroutine-Intensive Industries

Independent Variables	Routine-intensive Industries	Nonroutine-intensive Industries
α_C	0.701*** (0.195)	0.377* (0.230)
α_K	−2.85 (2.95)	0.783*** (0.238)
α_{Lh}	1.265*** (0.146)	0.192*** (0.025)
α_{Lm}	0.964*** (0.340)	0.411* (0.225)
α_{Ll}	0.741*** (0.155)	0.265* (0.152)
β_{CC}	0.036*** (0.014)	0.034*** (0.009)
β_{CK}	−0.119*** (0.029)	−0.023 (0.021)
β_{CLh}	−0.093*** (0.020)	0.009** (0.004)
β_{CLm}	0.087** (0.041)	−0.011 (0.020)
β_{CLl}	−0.019 (0.024)	0.014 (0.009)
β_{KK}	0.257*** (0.023)	0.037** (0.018)
β_{KLh}	−0.038* (0.022)	−0.005 (0.012)
β_{KLm}	−0.033 (0.051)	−0.018 (0.023)
β_{KLl}	−0.034 (0.025)	−0.005 (0.013)
β_{LhLh}	0.070*** (0.014)	0.016** (0.007)
β_{LhLm}	0.030 (0.051)	−0.029 (0.028)
β_{LhLl}	−0.103*** (0.028)	−0.022** (0.011)
β_{LmLm}	−0.158*** (0.056)	0.061** (0.028)

β_{LmLl}	0.134** (0.064)	−0.083*** (0.031)
β_{LlLl}	−0.048** (0.019)	0.041*** (0.009)
N	439	443

Notes: ****p*<0.01, ***p*<0.05, **p*<0.1. Industry and year dummies as well as average work experience for the three education levels are suppressed for brevity. Standard errors are in parentheses.

Table A5. Estimated Coefficients for High-AIE vs. Low-AIE Industries

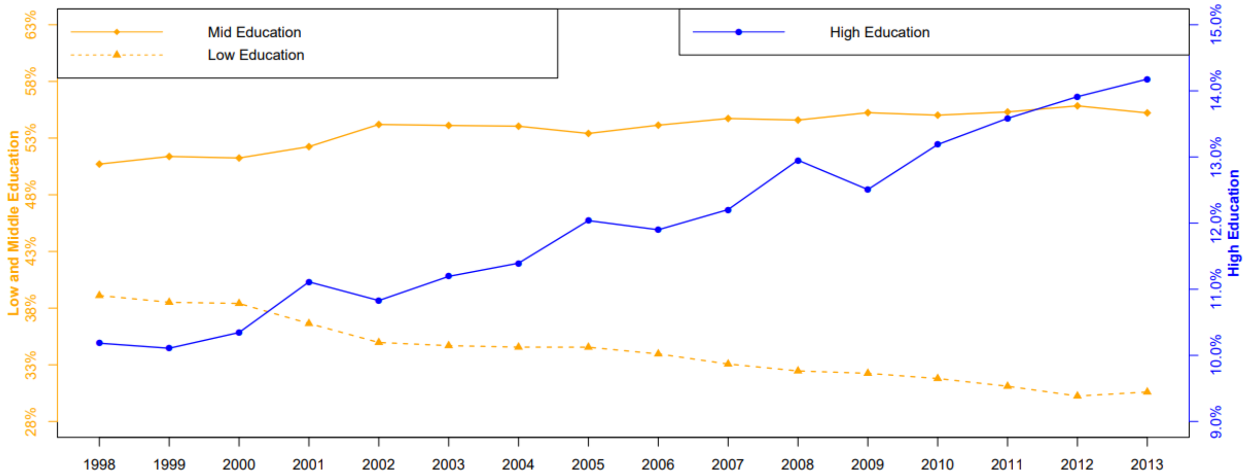
Independent Variables	**High-AIE Industries**	**Low-AIE Industries**
α_C	0.550*** (0.197)	0.331*** (0.083)
α_K	0.303 (0.406)	2.473*** (0.576)
α_{Lh}	1.282*** (0.202)	0.282* (0.164)
α_{Lm}	0.016** (0.008)	1.358** (0.533)
α_{Ll}	0.874*** (0.328)	0.330** (0.173)
β_{CC}	−0.007 (0.012)	0.003 (0.022)
β_{CK}	−0.045** (0.023)	−0.016 (0.035)
β_{CLh}	−0.036* (0.021)	0.006** (0.003)
β_{CLm}	0.055 (0.038)	−0.006 (0.054)
β_{CLl}	0.008 (0.025)	0.015 (0.043)
β_{KK}	0.028 (0.018)	−0.081*** (0.027)
β_{KLh}	−0.024 (0.019)	−0.019 (0.015)
β_{KLm}	−0.056* (0.033)	−0.027 (0.045)
β_{KLl}	0.055** (0.027)	−0.021 (0.039)
β_{LhLh}	0.076*** (0.018)	0.021** (0.010)
β_{LhLm}	−0.094* (0.052)	0.081** (0.040)
β_{LhLl}	−0.103*** (0.030)	−0.105*** (0.027)
β_{LmLm}	0.073 (0.052)	−0.133** (0.065)

β_{LmLl}	−0.012 (0.050)	0.071 (0.097)
β_{LlLl}	0.066*** (0.020)	0.056 (0.040)
N	417	406

Notes: ***p<0.01, **p<0.05, *p<0.1. Industry and year dummies as well as average work experience for the three education levels are suppressed for brevity. Standard errors are in parentheses.

Appendix G: Percentages of Labor Inputs over Time based on AI Exposure and STEM Intensity

Figure A1. Percentages of Labor Inputs over Time (High-AIE Industries)



Note: The scale for high-education labor is on the right and that for low- and middle-education levels on the left. Same for Figures A2, A3, and A4.

Figure A2. Percentages of Labor Inputs over Time (Low-AIE Industries)

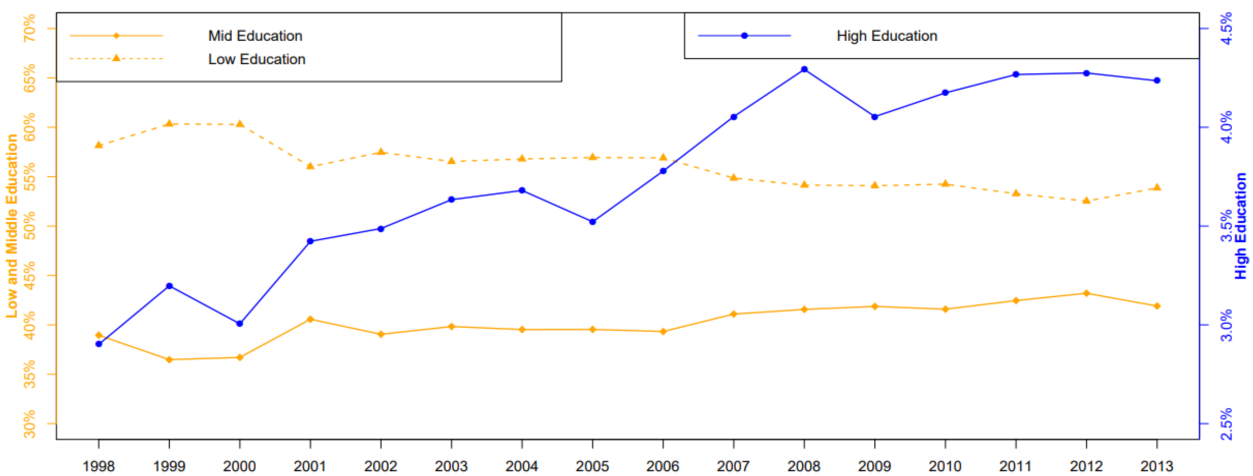


Figure A3. Percentages of Labor Inputs over Time (High-STEM Industries)

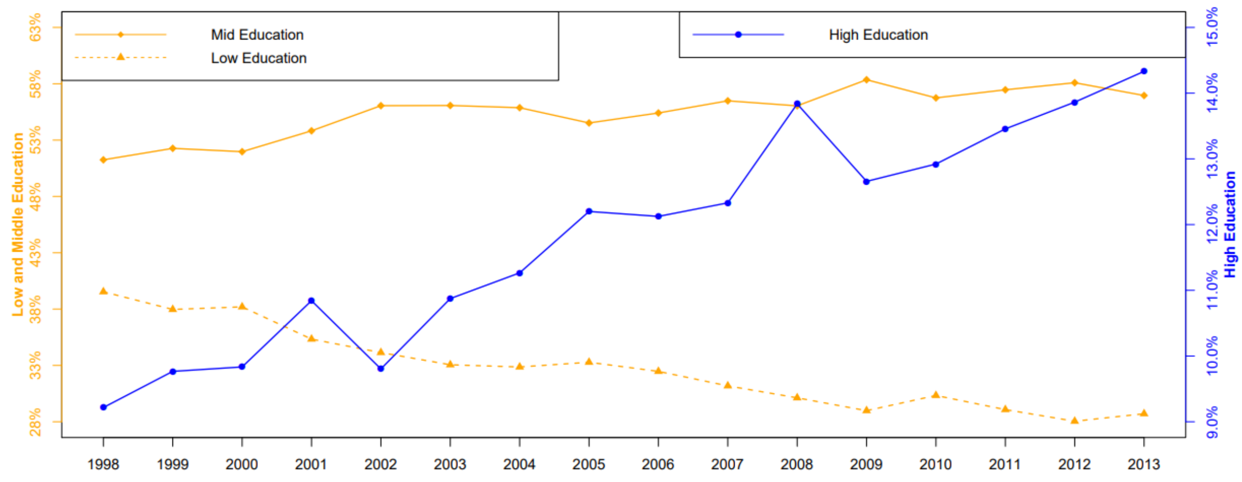
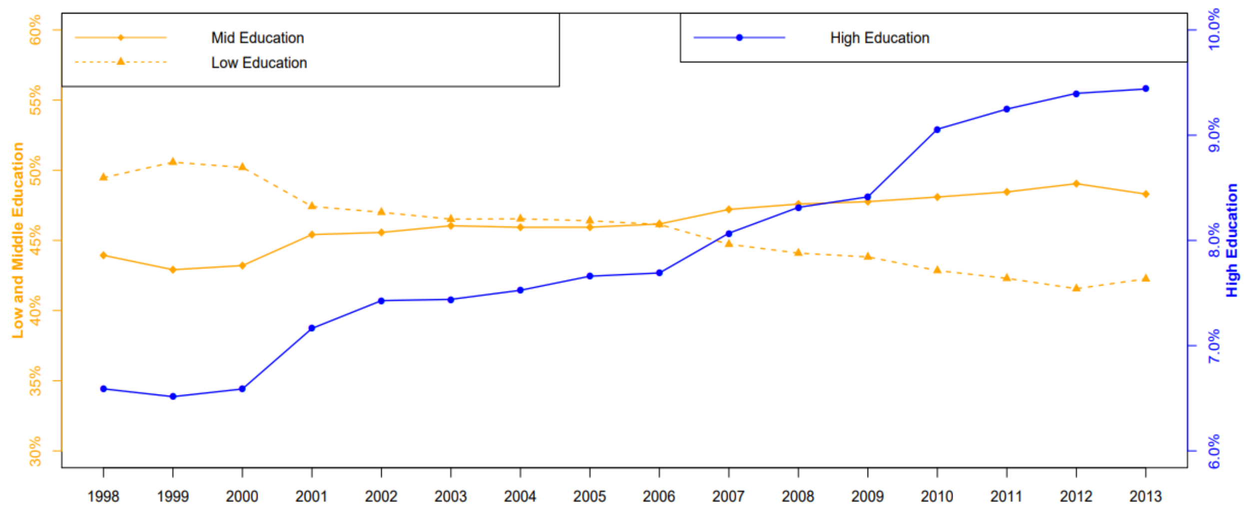


Figure A4. Percentages of Labor Inputs over Time (Low-STEM Industries)



Appendix H: The Impact of STEM Occupations

Our study is also related to the broad literature on STEM occupations. STEM refers to the academic fields of science, technology, engineering, and mathematics. STEM fields and occupations have long been viewed as drivers of innovation and catalysts of economic growth and competitiveness (Waite and McDonald 2019; Winters 2013). STEM workers have specialized skills that support research and development activities, increasing the productivity of all workers in the economy. STEM occupations can work on tasks that could be either manual or cognitive by nature and exist in both manufacturing and service industries. Increasing the size of the STEM workforce has been a key strategy to maintain the economic competitiveness and growth of the U.S. economy (Korte et al. 2019).

There has been an established literature on the how to address to the growing demand for STEM education (Castleman et al. 2018; Waite and McDonald 2019), importance of STEM education to wage and economic growth and global competition (Black et al. 2021; Cover et al. 2011; Stewart et al. 2020; Winters 2013), gender disparity on STEM performance (Anaya et al. 2022), and the impact of STEM immigrants on domestic workers and the local economy (Cai and Winters 2017; Gunadi 2019; Ransom and Winters 2021; Turner 2022). However, to the best of our knowledge, there has been little empirical evidence from prior literature on how STEM occupations may moderate the relationship between technology and labor. To this regard, we divide all industries into those with relatively higher and lower percentages of STEM workers.

To derive the percentages of STEM workers for each industry, we follow the same approach that we use to derive the routine/nonroutine intensive industries (see Section 4.2.3 in the paper). We first identified the STEM occupations using the US Census Bureau STEM Occupation Code.[1] Then, for all employees in the CPS surveys, we categorized them into STEM or non-STEM employees and calculated the percentage of STEM employees in each industry. We use the median STEM percentage in our sample to divide all industries into high-STEM and low-STEM industries. A complete classification of the high- and low-STEM industries is presented in Online Appendix D. We note that 39% of the high-STEM

[1] https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html

industries are nonroutine industries, and 56% of the low-STEM industries are nonroutine. The percentages of labor inputs for high-STEM and low-STEM subsamples are presented in Online Appendix G.

Conceptually, in high-STEM industries, workers are trained to be better prepared to work with IT, particularly for those with higher-education level. Table A6 in Online Appendix H presents the FGLS estimation results for Equation (4) for high-STEM and low-STEM subsamples. The AES and MES estimates for high- versus low-STEM industries are present in Table A7. For the high-STEM industries, IT is a strong complement with high-education labor but a substitute for low- and middle-education labor; for low-STEM industries, IT and labor are substitutes regardless of education levels. These results suggest that for industries that require a relatively higher level of STEM skills, IT is replacing low- and middle-education level labor but complementing high-education labor; for the industries requiring a relatively lower level of STEM skills, IT is replacing labor of all education levels. This is likely because, while high-education labor and IT tend to be complements in general (Griliches 1969), this complementarity is hard to materialize in low-STEM industries, primarily because the high-education labor in these industries may not have the sufficient skills to make effective use existing technologies as well as to explore the introduction and implementation of new technologies.

Table A6. Estimated Coefficients for High-STEM vs. Low-STEM Industries

Independent Variables	High-STEM Industries	Low-STEM Industries
α_C	1.106*** (0.211)	0.502** (0.234)
α_K	1.588*** (0.257)	−1.112 (0.801)
α_{Lh}	0.152* (0.810)	1.003*** (0.136)
α_{Lm}	0.953** (0.402)	0.476** (0.197)
α_{Ll}	−0.401*** (0.144)	−0.389* (0.201)
β_{CC}	0.021 (0.027)	0.037** (0.016)
β_{CK}	−0.135*** (0.033)	−0.101*** (0.029)
β_{CLh}	−0.054* (0.031)	0.004 (0.014)
β_{CLm}	0.039 (0.083)	0.031 (0.035)
β_{CLl}	0.042** (0.021)	−0.007 (0.024)
β_{KK}	0.008 (0.015)	0.099*** (0.029)
β_{KLh}	0.036 (0.023)	−0.024** (0.012)
β_{KLm}	−0.064 (0.048)	0.032 (0.038)
β_{KLl}	0.031 (0.040)	−0.021 (0.030)
β_{LhLh}	0.027* (0.015)	0.052*** (0.010)
β_{LhLm}	0.088* (0.053)	−0.086** (0.043)
β_{LhLl}	−0.132*** (0.032)	−0.090*** (0.026)
β_{LmLm}	−0.030 (0.071)	−0.068 (0.057)
β_{LmLl}	−0.051 (0.090)	0.036 (0.070)
β_{LlLl}	0.056 (0.034)	0.086*** (0.026)
N	437	445

Notes: ***p<0.01, **p<0.05, *p<0.1. Industry and year dummies as well as average work experience for the three education levels are suppressed for brevity. Standard errors are in parentheses.

Table A7. Interpretation of the AES_*ij* and MES_*ij* Estimates: High- vs. Low-STEM Industries

Input *i*	Input *j*	High-STEM Industries			Low-STEM Industries		
		AES_*ij*	MES_*ij*	Interpretation	AES_*ij*	MES_*ij*	Interpretation
C	*Lh*	−1.016*** (0.099)	−0.027*** (0.001)	Strong Complements	1.989*** (0.072)	0.198*** (0.028)	Substitutes
C	*Lm*	1.600*** (0.155)	0.232*** (0.017)	Substitutes	1.047*** (0.077)	0.612*** (0.020)	Substitutes
C	*Ll*	2.205*** (0.123)	0.537*** (0.075)	Substitutes	2.421*** (0.192)	1.377*** (0.069)	Substitutes
Lh	*C*	−1.016*** (0.099)	−1.370*** (0.036)	Strong Complements	1.989*** (0.072)	0.053*** (0.007)	Substitutes
Lm	*C*	1.600*** (0.155)	1.092*** (0.028)	Substitutes	1.047*** (0.077)	0.360*** (0.045)	Substitutes
Ll	*C*	2.205*** (0.123)	1.971*** (0.045)	Substitutes	2.421*** (0.192)	0.030*** (0.007)	Substitutes

Notes: *C* is IT capital; *Ll*, *Lm*, and *Lh* are low-education, middle-education, and high-education labor, respectively.

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