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Completed Research Paper

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Abstract

The tenet of artificial intelligence (AI) is to use machines to replace humans in performing tasks while the conviction of intelligence augmentation (IA) is to use machines to assist and enhance humans in performing tasks. This paper argues that the relationship between IT and human labor is more nuanced than what has been conceptualized in literature—IT not only can substitute for human labor (the AI effect) but also can complement it (the IA effect); the exact nature depends on the tasks to be performed and the education levels of the employees. We test these predictions using an industry-level dataset covering 60 US industries from 1998 to 2013. The findings reveal co-existence of the AI and the IA effects during the sample period, and that education plays a critical role for workers to benefit from the massive adoption of IT by the US industries.

Keywords: information technology, human labor, artificial intelligence, intelligence augmentation, substitution, complementarity, elasticity of substitution

Introduction

The advancement of information technology (IT) has fundamentally changed our life and the world. Coupled with large amount of data and improved algorithms, IT has fueled the development of artificial intelligence (AI), where computer systems can mimic human brains to perceive environment and take actions to successfully achieve their goals. Today AI has been extensively applied in various scenarios such as self-driving cars, drones, and robotics, and thus it is quickly replacing humans in performing many tasks. Some scientists and business leaders even conclude that all human jobs would disappear in less than 20 years (Brown 2016), and fully development of AI could spell the end of the human race because humans are limited by slow biological evolution and could not compete with AI (Sainato 2015). On the other hand, many others believe that computers and human brains have their strengths and weaknesses, and important problems are often solved by humans and computers working cooperatively through intelligence augmentation (IA), where IT is used to assist and enhance human intelligence in performing tasks (Licklider 1960). In the eyes of proponents of IA, IT complements and supports human thinking, analysis, and planning, but leaves humans at the center of task performance or decision-making.

The debate between AI and IA has been going on for over several decades (Lavenda 2016). At the center of the debate is what kind of roles IT and human labor play respectively in performing tasks and achieving goals: are IT and human labor complements or substitutes? From the perspective of AI, the substitution effect dominates, while the complementarity effect dominates from the perspective of IA. Therefore, critical questions remain: have we been witnessing more of a substitution or complementarity between IT and labor over the past twenty years? Which effect dominates, AI or IA? Understanding these questions not only makes theoretical contributions, but also bears critical implications for various stakeholders, including individuals, firms, and government agencies.

Although factor substitution/complementarity can be examined through different approaches, the one that is most relevant to this study is elasticity of substitution (ES) between production factors — how the input level of one factor influences the input level of another, holding output level constant. Information systems (IS) researchers adopting this approach predominantly find a substitution effect between IT and human labor in the production process (Chwelos et al. 2010; Dewan and Min 1997; Hitt and Snir 1999; Zhang et al. 2015). In other words, prior IS literature predominantly supports the AI perspective of the impact of IT.

However, while prior studies have significantly deepened our understanding of the issue, key research gaps remain. First, virtually all prior studies consider human labor as a monolithic whole when examining the interaction between IT and labor, ignoring the possibility that IT may have different impact on various types of labor. Second, prior studies typically apply Allen elasticity of substitution (AES) to estimate the substitution/complementarity effect. As we discuss later, AES has some major limitations and a better metric is the Morishima elasticity of substitution (MES), which has been largely overlooked in IS literature, with the exception of Zhang et al. (2015). Moreover, the estimates from AES and MES are not always consistent, and when this happens, how do we reconcile their differences?

Therefore, it is our goal in this study to bridge these gaps by: 1) stratifying labor into three different education levels and estimate their interaction with IT separately and 2) applying AES and MES jointly to offer an intuitive interpretation of the ES results based on the production function framework. In so doing, we intend to show a more complete and nuanced picture on the interaction between IT and labor, and thus unravel the debate between the AI and IA perspectives regarding IT’s impact on labor.

Background, Theories, and Hypotheses

Production theory from economics posits that firms minimize cost in the production process, and during this process, firms adjust the amount of input factors according to the price change of the input factors. Two factors are complements/substitutes if an increase in use of one factor raises/decreases the input of another factor. This tradeoff between input factors is captured through the metric of elasticity of substitution (ES).

Information technology (IT) — broadly defined as computers as well as related digital communication technology—has greatly changed many aspects of today's world. The impact of IT can be felt everywhere from individuals, businesses, to governments and society. As IT excels human beings in its processing capability and communication capability, it is widely believed that IT may substitute for human labor in carrying out various tasks.

Indeed, there have been anecdotal evidence and case studies supporting this view. For example, World Bank estimates that 57% of jobs in the OECD countries could be automated over the next two decades (World Bank Group 2016). Acemoglu and Restrepo (2017) find that one more robot per thousand workers reduces the employment to population ratio by about 0.18% to 0.34% and wages by 0.25% to 0.5%.

IS researchers have also shown great interests in examining how IT affects labor input in the production process. For example, by estimating the ES of various production functions, Dewan and Min (1997) find that IT not only substitutes for labor input but also non-IT capital input. Also estimating production functions, Hitt and Snir (1999) find that while IT may complement non-IT capital input in modern organizations, it consistently substitutes for labor input across all organizations. Similarly, Chwelos et al. (2010) find IT complements non-IT capital investment in more recent years, but IT has been consistently substituting for labor in the production process. All three studies used AES as the metric for substitution/complementarity effect. However, AES has some major limitations, and MES is gaining popularity. Zhang et al. (2015) estimate both AES and MES, and they reach the same conclusion that IT is a substitute for labor input. The findings from these studies are summarized in Table 1 below:

Table 1. Prior Findings Using AES or MES from the IS Literature

Studies	**Method**	**Time Period**	**Key Findings**	**IT vs Non-IT Capital**	**IT vs Labor**
Dewan and Min (1997)	AES	1985-1993	IT is a perfect substitute for both non-IT capital and labor in all sectors of the economy.	Substitutes	Substitutes
Hitt and Snir (1999)	AES	1995-1996	IT and non-IT capital are substitutes in traditional organizations while they are complements in modern organizations; IT and labor are consistently substitutes across all organizations.	Substitutes/ Complements	Substitutes
Chwelos et al. (2010)	AES	1987-1998	IT and non-IT capital are complements while IT and labor are substitutes.	Complements	Substitutes
Zhang et al. (2015)	AES and MES	1998-2009	IT is a substitute for both non-IT capital and labor	Substitutes	Substitutes

We first examine labor force of middle-education level. It has been observed that workers of middle-education level typically perform routine tasks, which can be manual or cognitive in nature, as in occupations such as machine operators, material handlers, accountants, and bank clerks (Acemoglu and Autor 2011; Beaudry et al. 2016; Manning 2004; Michaels et al. 2014). Routine tasks basically follow rule-based logic and can be easily programmed and delegated to computers and machines. As IT capability continues to advance, middle-education labor that perform routine tasks are more and more likely to be automated by AI. Take bookkeeping tasks for example, with the introduction of digital platforms that could automate a large part of data collection and data processing, we are witnessing a fast decline of bookkeeping jobs over time (Stebbins and Sauter 2016). Autor et al. (2002) also show that the number of office clerks in banks, a typical type of middle-education workers, has declined over time as a result of the wide adoption of computer-based tools. Research from AI, robotics, and cognitive science all point out that the routine tasks performed by middle-education labor can be programmed and delegated to computers and machines (Ford 2013; Pinker 1994). Over the past few decades, as the price of computers continues to drop sharply, more IT investment is made and technologies deployed to replace labor of middle education level since IT can be used to perform the same types of tasks as human beings, only better, faster, and cheaper (Brynjolfsson and Hitt 2000). Thus, we propose the following:

H1: *IT substitutes for human labor of middle education level in the production process*.

The second group we examine is labor force of high-education level. Prior studies have suggested that the skill-biased technological change (SBTC) in recent decades has shifted labor demand towards more skilled workers, who are better prepared to participate in the economic, political, and social activities, and engage in complex, technology-oriented dimensions of today's economy (Goldin and Katz 1998). Employees of high education are more likely to work on cognitive and nonroutine tasks that are typically performed by engineers, consultants, executives, and physicians (Acemoglu and Autor 2011; Beaudry et al. 2016; Manning 2004; Michaels et al. 2014).

The commonality of these tasks is that they are hard to be programmed, and they normally involve dealing with semi- or unstructured problems. For this reason, computers cannot at present readily carry out these tasks, despite the fact that they are increasingly used at workplace due to precipitous price drop. Rather than substituting for human labor, IT investment complements human labor in performing these tasks since these tasks are information-intensive and require expert thinking, complex communication, and coordination. In other words, increased input of IT capital actually demands more input of highly educated and skilled labor. For example, adoption of data analytics in business has triggered large demand for data scientists for many companies such as Amazon and Capital One (Davenport 2006). This complementarity effect can also be derived from the balanced production theory. As we have discussed earlier, computers can be used to automate routine and repetitive work. However, for work that cannot be fully automated, or human intervention is not completely dispensed of, increased input of IT capital requires more labor performing abstract tasks, since the output of computers and output of humans need to be paired up and balanced (Baumol 1967; Kremer 1993). This indicates that IT becomes a complement to human labor of high education in the production process. Therefore:

H2: *IT complements human labor of high education level in the production process*.

The last group is employees of low education level. Technology was initially adopted mainly to automate routine tasks performed by low-skilled labor and thus had been a net substitute to low-education labor. There are two reasons for this: first, these tasks are routine and thus become easy targets for automation compared to non-routine tasks, and second, these jobs are the easiest to automate among all routine jobs because they require less skills. For example, telephone operators were replaced by automatic switching devices and drive-through banking was replaced by ATM machines. Other examples include factory assemblers, elevator operators, and grocery store cashiers, etc. This substitution pattern was also reported in prior studies. For example, Berndt et al. (1992) find substantial decrease of workers without a high-school degree during 1968-1986, and Autor et al. (1998) find consistent decline of labor of high-school dropouts through the 1990s. Over time, IT capability has been advancing with fast paces in such areas as processing capability, communication capability, and storage capability. At the same time, application algorithms have also witnessed significant improvement. Consequently, low-skilled labor that can be routinized and automated through AI keeps expanding. For example, janitors and house cleaners, two typical types of low-education workers, were considered to be extremely hard to automate (Levy and Murnane 2004), but recent inventions such as household robots are increasingly adopted to do household chores. Similarly, jobs by waiters and bartenders were considered to be hard to automate; but today more and more restaurants and fast food chains are using self-service kiosks to serve customers. Therefore, we predict that to generate the same amount of output, less labor of low education will be required as more IT is adopted.

H3: *IT substitutes for human labor of low education level in the production process*.

Methods and Data

Estimation methods

To test our hypotheses, we need to adopt appropriate estimation methods. As mentioned earlier, the method of ES is most appropriate for this study since it uses the production function framework and accounts for the tradeoff between input factors given the same level of output; this way we can examine how IT and labor are interacting in the production process. Another advantage of our ES approach is that it can take into account the price changes of input factors; this is particularly attractive given the precipitous price drop of computing equipment over time (Ba and Nault 2017).

For an n-input production function $Y = f(x)$, where Y is the output and x is the vector of inputs, for constant output, the rate at which input *i* can substitute for input *j* is described as the marginal rate of technical substitution (MRTS):

$$\partial x_i / \partial x_j = -\frac{\partial f(x) / \partial x_j}{\partial f(x) / \partial x_i} = -f_j / f_i ,$$

where f_i is the partial derivative of $f(x)$ with respect to x_i. However, MRTS does not incorporate the impact of prices, and to do so we need to introduce the elasticity of substitution (ES), defined as the percentage change in the input ratio in response to the percentage change in MRTS (Hicks 1932):

$$\sigma = \frac{d(x_i / x_j)/[x_i / x_j]}{d(f_j / f_i)/[f_j / f_i]}$$

The Allen elasticity of substitution (AES) generalizes the ES to the n-factor case (Uzawa 1962). The AES between inputs *i* and *j* is given as:

$$\sigma_{ij}^{A} = \frac{\sum_i x_i f_i}{x_i x_j} \frac{\mathbf{H_{ij}}}{\mathbf{H}} \tag{1}$$

where $\mathbf{H}$ is the bordered Hessian determinant of $f(x)$, and $\mathbf{H_{ij}}$ is the cofactor associated with f_{ij}. Inputs *i* and *j* are substitutes if $\sigma_{ij}^{A} > 0$, meaning an increase in the price of *j* decreases the input quantity of *j* but increases the input quantity of *i*; and inputs *i* and *j* are complements if $\sigma_{ij}^{A} < 0$. AES measures the amount of change in one input factor due to a price change of another input factor, holding output and all other input prices constant, and this corresponds exactly to what we state in the hypotheses. Prior research in IS has used AES to determine whether IT and other production factors are complements or substitutes (Chwelos et al. 2010; Dewan and Min 1997; Hitt and Snir 1999). However, one major drawback of AES is that it is symmetric so that $\sigma_{ij}^{A} = \sigma_{ji}^{A}$, and thus does not consider which input's price is changing. Moreover, AES is not informative beyond the fact that it has the same sign as the cross-price elasticity of demand (Blackorby and Russell 1989).

Overcoming these drawbacks of AES, the Morishima elasticity of substitution (MES) is constructed as:

$$\sigma_{ij}^{M} = \frac{f_j}{x_i} \frac{\mathbf{H_{ij}}}{\mathbf{H}} - \frac{f_j}{x_j} \frac{\mathbf{H_{jj}}}{\mathbf{H}} \tag{2}$$

where σ_{ij}^{M} measures the change in input *i* relative to input *j* as a result of a price change in input *j*. When $\sigma_{ij}^{M} > 0$, inputs *i* and *j* are substitutes, meaning that an increase in the price of *j* increases the quantity ratio of input *i* over input *j*. When $\sigma_{ij}^{M} < 0$, inputs *i* and *j* are complements. In addition, MES is asymmetric, so that $\sigma_{ij}^{M} \neq \sigma_{ji}^{M}$. Therefore, MES measures the change in the quantity ratio between two inputs when price of one of the inputs is changing. MES provides an important tool for assessing tradeoffs in the mix of inputs when input price changes over time differ so widely as in the case of the sharp falling of the price of IT capital in contrast to the steady increase of the prices of labor and other capital (Ba and Nault 2017).

As shown by prior research, AES can be expressed as $\sigma_{ij}^{A} \propto \partial \ln x_i / \partial \ln p_j$ (Blackorby and Russell 1989) and MES as $\sigma_{ij}^{M} = \partial \ln[x_i / x_j] / \partial \ln p_j$ (Chambers 1988). Therefore, AES has the same sign as the cross-price elasticity of demand even though its magnitude is relatively uninformative, and MES represents relative quantity change in response to a price change of an input. We use signs from both the AES and MES to determine whether IT and labor are substitutes or complements, and use the magnitude of MES to access the strength of this relationship. To the best of our knowledge, we are the first to use AES and MES jointly to determine and interpret the substitution/complementarity relationship between production inputs. Table 2 provides an intuitive interpretation of the joint AES and MES results.

Table 2. Interpretation of the AES and MES Estimates[1]

AES_*ab*	MES_*ab*	
+	+	Substitutes
−	+	Weak Complements
−	−	Strong Complements

In Table 2, AES_*ab* is the AES between input *a* and input *b*. MES_*ab* is the MES between input *a* and input *b* when the price of *b* changes. When both AES and MES are positive, input *a* and input *b* are substitutes. It becomes more interesting when the signs of AES and MES differ. When AES is negative and MES is positive, input *a* and input *b* become complements. In this case, the percentage change in input *a* is always smaller than the percentage change in input *b* when the price of input *b* changes, and thus we define input *b* as a "weak complement" with input *a*. When both AES and MES are negative, input *b* becomes a "strong complement" with input *a* as the percentage change in input *a* is greater than the percentage change in input *b* as a result of a change in the price of input *b*.

Before we are able to estimate the AES and MES, we need to choose a production function from which the coefficient estimates are used as inputs to calculate the AES and MES. We adopt a flexible functional form, the Translog function with labor of three education levels:

$$\begin{aligned}\log(V) &= \delta + \alpha_c \log C + \alpha_K \log K + \alpha_{Lh} \log Lh + \alpha_{Lm} \log Lm + \alpha_{Ll} \log Ll + \beta_{CC} (\log C)^2 \\ &+ \beta_{CK} \log C \log K + \beta_{CLh} \log C \log Lh + \beta_{CLm} \log C \log Lm + \beta_{CLl} \log C \log Ll + \beta_{KK} (\log K)^2 \\ &+ \beta_{KLh} \log K \log Lh + \beta_{KLm} \log K \log Lm + \beta_{KLl} \log K \log Ll + \beta_{LhLh} (\log Lh)^2 + \beta_{LhLm} \log Lh \log Lm \\ &+ \beta_{LhLm} \log Lh \log Ll + \beta_{LmLm} (\log Lm)^2 + \beta_{LmLl} \log Lm \log Ll + \beta_{LlLl} (\log Ll)^2 + \varepsilon \end{aligned} \quad (3)$$

where V is value added, C is IT capital, K is non-IT capital, Lh is high-education labor, Lm is middle-education labor, and Ll is low-education labor. Using coefficient estimates from the Translog production function (3), we could further calculate estimates for AES and MES. The specific steps to calculate AES and MES for the Translog function are not included due to page limitation, but are available upon request.

Data

Our hypothesis testing is conducted at the industry level for the US economy. We acquired and merged industry-level data on value added, IT capital, and non-IT capital from two sources: the

[1] Mathematically, the case of "+" and "—" does not exit.

Bureau of Labor Statistics (BLS) and the Bureau of Economic Analysis (BEA). The dataset covers 60 US industries for 16 years from 1998 to 2013. The industry categories are based on the 2007 North American Industry Classification System (NAICS) and are at the three-digit level. All value-based variables have been converted to constant 2009 dollars using chain-type quantity indices provided by the BEA.

Specifically, value added (V) is the gross output net of total intermediate inputs. IT capital (C) is the aggregate stock of information processing equipment and software. Non-IT capital (K) is obtained by subtracting IT capital from the total stock of private fixed assets. Labor (L) is the number of total full-time equivalent employees.

To stratify labor input L into different groups by education levels, we make use of a third dataset: the US Current Population Survey (CPS) annual demographic survey conducted in March each year. The CPS is a monthly survey of US households conducted by the Bureau of Census and the Bureau of Labor Statistics, and it is the primary source of labor force statistics for the US population. Currently there are more than 60,000 households and over 140,000 individuals surveyed in each month. The survey identifies employees who are in the labor force, their industry sectors, and their education levels. Therefore, for each industry, we are able to group all employees into one of three groups based on their highest education levels: low, middle, and high. Low-education level is high school or below, middle-education level is associate or college degree, and high-education level is master's degree or above. We then calculate the percentages of each group of employees in the CPS industries, and then match the CPS industries to the NAICS-based industries for each corresponding year. Finally, given the labor input of each NAICS industry and the percentages of employees of the three education levels from the CPS, we can calculate the input of low-, middle-, and high-education labor to obtain Ll, Lm, and Lh, respectively. Figure 1 below provides the time trend for the percentages of Ll, Lm, and Lh in the labor force. Overall, Lm has consistently been the largest proportion of the labor force since 2000, and Lh consistently take the smallest proportion of the labor force. The percentages of Lh and Lm are increasing over the years, whereas that for Ll has been decreasing. Table 3 provides the summary statistics for our variables.

Figure 1. Time Trend for Labor Input Proportions

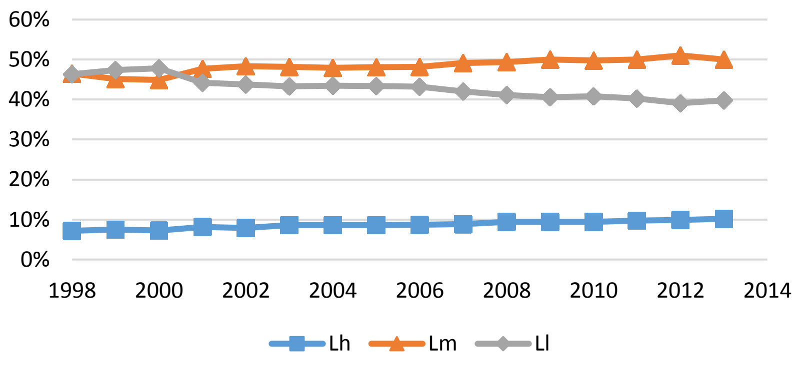


Table 3. Summary Statistics (N=939)

Variable	Mean	Std. dev.	Min.	Max.
Value Added (V)	205,987	270,856	5,511	1,865,536
IT Capital (C)	24,559	45,787	514	406,635
Non-IT Capital (K)	254,424	305,216	12,909	1,814,622
High-education Labor (Lh)	159	265	0	2,301
Middle-education Labor (Lm)	850	1,113	0	8,332

Low-education Labor (*Ll*)	724	1,206	0	7,329

Notes: Labor variables are in thousands of full-time equivalent employees; *V*, *C*, and *K* are in millions of 2009 dollars.

Estimation Results

Baseline Results

As we have a panel dataset, we estimate three models using the feasible generalized least squares (FGLS) panel model, adjusting for heteroscedasticity and panel-specific autocorrelation. The results are presented in Table 4. Specifically, column 2 presents results for the 3-input Cobb-Douglas production function, column 3 the 3-input Translog production function and column 4 the 5-input Translog function which is in Equation (3). We also include industry and year dummies as additional independent variables to control for the fixed effects.

It can be seen that the estimates from both the Cobb-Douglas and Translog production functions are consistent with results from prior literature (Chwelos et al. 2010; Zhang et al. 2015).

Table 4. Estimated Coefficients from the Production Functions

Independent Variables	3-Input Cobb-Douglas	3-Input Translog	5-Input Translog
α_C	0.107*** (0.015)	0.495*** (0.163)	0.706*** (0.144)
α_K	0.354*** (0.019)	0.187 (0.390)	−0.308 (0.243)
α_L	0.549*** (0.019)	2.301*** (0.205)	
α_{Lh}			0.289*** (0.077)
α_{Lm}			0.657*** (0.169)
α_{Ll}			0.297*** (0.073)
β_{CC}		0.033*** (0.205)	0.029*** (0.006)
β_{CK}		−0.061*** (0.016)	−0.098*** (0.014)
β_{CL}		−0.034** (0.014)	
β_{CLh}			−0.017** (0.007)
β_{CLm}			0.018 (0.015)
β_{CLl}			−0.001 (0.007)
β_{KK}		0.058*** (0.018)	0.074*** (0.012)
β_{KL}		−0.105*** (0.018)	
β_{KLh}			−0.002 (0.008)
β_{KLm}			−0.041** (0.016)

β_{KLl}			0.001 (0.008)
β_{LL}		−0.015* (0.009)	
β_{LhLh}			0.027*** (0.006)
β_{LhLm}			−0.018 (0.022)
β_{LhLl}			−0.042*** (0.011)
β_{LmLm}			0.022 (0.024)
β_{LmLl}			−0.044* (0.024)
β_{LlLl}			0.026*** (0.007)

Notes: N=939; ****p*<0.01; ***p*<0.05; **p*<0.1. Industry and year dummies are suppressed for brevity. Standard errors are in the parenthesis.

Using the coefficient estimates from Table 4, we further calculate the AES and MES. The results are shown in Tables 5 and 6. Specifically, Table 5 presents the medians of AES and MES for the Cobb-Douglas production function with three inputs: IT capital (*C*), non-IT capital (*K*), and Labor (*L*). Table 6 presents the medians of AES and MES for the Translog production function with five inputs: IT capital (*C*), non-IT capital (*K*), high-education labor (*Lh*), middle-education labor (*Lm*), and low-education labor (*Ll*).

Table 5. Estimated AES and MES (3 Factors)

Elasticity	***a=C*** ***b=K***	***a=C*** ***b=L***	***a=K*** ***b=L***
AES_*ab*	3.597*** (0.352)	0.983*** (0.033)	1.603*** (0.020)
MES_*ab*	2.678*** (0.289)	1.196*** (0.011)	1.540*** (0.016)
MES_*ba*	2.344*** (0.197)	1.688*** (0.083)	1.983*** (0.061)

Note: Bootstrapped standard errors are in the brackets

Table 6. Estimated AES and MES (5 Factors)

Elasticity	***a=C*** ***b=K***	***a=C*** ***b=Lh***	***a=C*** ***b=Lm***	***a=C*** ***b=Ll***	***a=K*** ***b=Lh***	***a=K*** ***b=Lm***	***a=K*** ***b=Ll***
AES_*ab*	7.680** (3.210)	−0.955** (0.44)	2.865*** (0.191)	1.888*** (0.093)	1.933*** (0.215)	0.284*** (0.07)	0.793*** (0.119)
MES_*ab*	0.576*** (0.171)	0.044* (0.023)	1.686*** (0.041)	1.295*** (0.076)	0.487*** (0.11)	0.976*** (0.044)	0.998*** (0.043)
MES_*ba*	0.446*** (0.157)	−0.388*** (0.061)	0.208*** (0.066)	0.294*** (0.068)	0.519*** (0.163)	0.178* (0.102)	0.104** (0.045)

Note: Bootstrapped standard errors are in the brackets.

Recall that AES_*ab* is the AES between input *a* and input *b*. Due to the symmetrical design of AES, AES_*ab* is equal to AES_*ba*, and thus does not consider which input's price changes. MES_*ab* is the MES between input *a* and input *b* when the price of input *b* changes; MES_*ba* is the MES between the two inputs when the price of input *a* changes. Table 5 shows that all the AES and MES estimates are positive, and the results are consistent with finding from Dewan and Min (1997) and Zhang et al. (2015). Table 6 shows that AES_*CK*, MES_*CK*, MES_*KC*, AES_*CLh* and MES_*LhC* are negative, and all the rest of the elasticity measures are positive.

To intuitively interpret the above AES and MES results, we provide their qualitative interpretations in Table 7 below, with a focus on the relationship between IT and labor input.

Table 7 indicates that when the price of IT (*C*) changes, IT is a substitute for workers with a college degree or less, and a strong complement with those with a graduate degree or professional degree such as law and dentistry. Indeed, the price of IT has been falling drastically over the past few decades, and more firms are adopting IT to replace positions that require relatively less training and education. At the same time, the adoption of technologies drives up the demand for labor with more advanced degrees, who can do more sophisticated work that cannot be easily automated.

When the price of labor changes, we find largely similar results. When the price of low- and middle-education workers goes up (e.g., higher minimum wage), labor and IT become substitutes and more IT investment is well incentivized. When the price of high-education labor goes up, labor becomes a weak complement with IT and thus would reduce the utilization level of existing technologies.

Table 7. Interpretation of the AES and MES Estimates

	C	***L***	***Ll***	***Lm***	***Lh***
When price of *IT* changes		Substitutes	Substitutes	Substitutes	Strong Complements
When price of *L* changes	Substitutes				
When price of *Ll* changes	Substitutes				
When price of *Lm* changes	Substitutes				
When price of *Lh* changes	Weak Complements				

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

Our most striking finding is that IT and the middle-education labor — backbone of the “middle class” in a developed economy, have become substitutes regardless of which price is changing. This finding is different from prior literature which largely finds that technology and college-educated labor are complements (Bound and Johnson 1992), and reflects a trend in the IT-labor relationship where automation gradually replaces more work that used to be done by college-educated workers.

The above results from Table 7 show that H1 and H2 are supported — IT and middle-education workers are substitutes and IT and high-education workers are complements. In addition, H3 is also supported that IT and low-education workers are substitutes. In other words, our results suggest that for low- and middle-education labor, the AI effect of IT dominates; for high-education labor, the IA effect of IT dominates.

Time Trend for the Degree of Substitution/Complementation

There were events in our sample period (1998-2013) that could have an impact on the substitution/complementation relationship between the inputs. For example, the dot.com bubble burst around the year of 2000, and the financial crisis in 2008. In order to assess the time trend for the ES, we re-estimate the AES and MES using a series of two-year time windows. The reasons we adopt the two-year time windows are threefold: First, there are 16 years covered by our sample data and adopting a two-year time window would give us exactly 8 windows; Second, such division would allow us to explore the ES measures for the 2000-2001 and 2008-2009 periods separately; Third, a two-year time window is better than using an individual year because ES measures based on one year may not be robust enough. The results from using the two-year time windows are presented in Table 8. We also estimate the ES using three-year windows and the results stay qualitatively the same.

We offer the intuitive and qualitative interpretation of the results in Table 8 below, where "S" represents substitutes and "C" represents complements. Results from Table 8 show that, using a series of two-year time windows, IT is a substitute for low- and middle-education labor consistently over time, regardless of which price is changing. High-education labor, on the other hand, has consistently been a complement with IT regardless of which price is changing. These findings confirm our results from the pooled dataset. What is more interesting is how the magnitude of substitution/complementarity changes over time, which we discuss below.

We plot the MES estimates to observe the patterns over time. Figure 2 uses the values of MES_ *LlC* and MES_ *LmC* from Table 8. It shows that when the price of IT changes (price of IT has been dropping significantly over time), substitution for low-education labor has been consistently stronger than that for middle-education labor, except for the 08-09 period when the US economy was hit by the financial crisis. The gap between the two is the largest during the 00-01 period when the dot.com bubble burst, possibly because the level of IT investment hit historically high right around the year of 2000 and a large amount of traditional labor work were automated during that time. Here we define the IT investment made by firms due to the price drop of IT as *proactive IT investment* since firms would like to take advantage of the cheaper IT to substitute for relatively more expensive labor.

Table 8. Interpretation of the AES and MES Estimates by Two-Year Time Windows

Two-Year Windows	When Price of IT Changes			When Price of Labor Changes		
	Ll	*Lm*	*Lh*	*Ll*	*Lm*	*Lh*
1998-1999	S	S	Strong C	S	S	Weak C
2000-2001	S	S	Strong C	S	S	Strong C
2002-2003	S	S	Strong C	S	S	Strong C
2004-2005	S	S	Strong C	S	S	Strong C
2006-2007	S	S	Strong C	S	S	Weak C
2008-2009	S	S	Strong C	S	S	Strong C
2010-2011	S	S	Strong C	S	S	Strong C
2012-2013	S	S	Strong C	S	S	Weak C

Notes: *Ll*, *Lm*, and *Lh* are low-education, middle-education, and high-education labor, respectively.

Figure 2: Degree of Substitution over Time: When Price of IT Changes

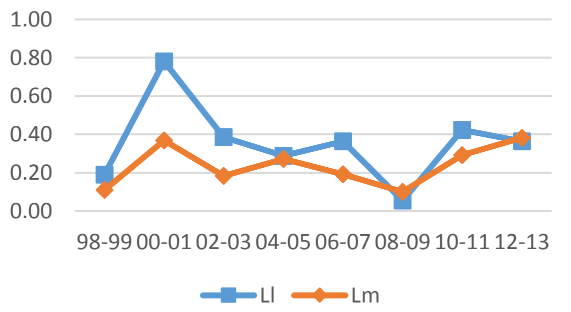


Figure 3: Degree of Substitution over Time: When Price of Labor Changes

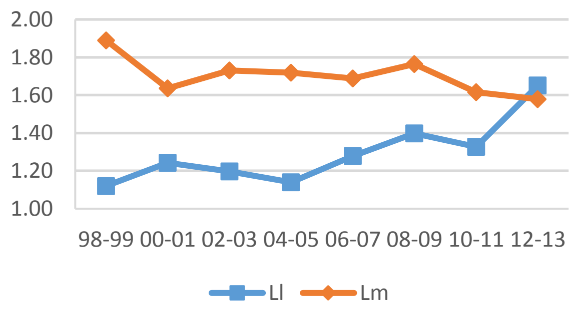
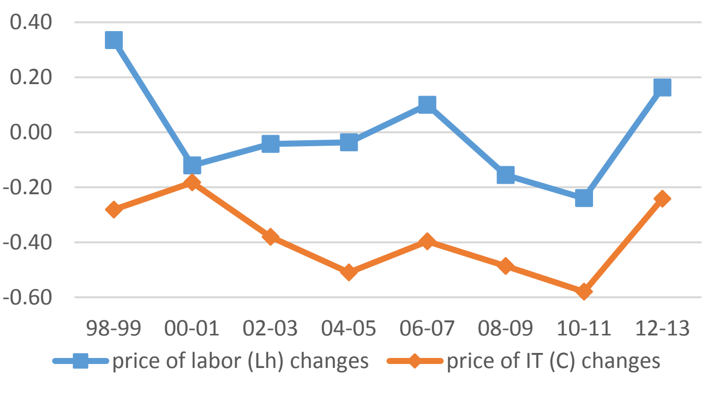


Figure 3 plots the values of MES_ *CLl* and MES_ *CLm* from Table 8. It shows that when price of labor changes (in general increasing over time, but with a much slower pace than changes in IT price), substitution by IT for middle-education labor is much stronger than that for low-education labor, except for the 12-13 period. This is a very interesting result because it indicates that the middle-education labor actually suffers the most when the average labor cost goes up—firms have strong incentives to react to such higher cost by investing in technology and automation. Moreover, both substitution lines are higher than unity, which means they are stronger than the two substitutions in Figure 2. Here we define the IT investment made by firms due to labor wage increase as *reactive IT investment* since as labor becomes more expensive, firms choose to respond by investing in IT to automate jobs and substitute for more expensive labor.

Comparing Figure 3 to Figure 2, we see relatively weaker incentives for proactive IT investment as a result of the improving performance/price ratio of IT (as in Figure 2), and much stronger incentives for reactive IT investment responding to higher labor cost (as in Figure 3).

Figure 4 plots the values of MES_ *LhC* and MES_ *CLh* from Table 8. It shows that when it comes to high-education labor, the complementarity effect is much stronger when the price of IT changes, compared to that when the price of high-education labor changes (the more negative the MES measure, the stronger the complementarity). Interestingly, we have observed an increasing demand for high-education labor in recent years (Acemoglu and Autor 2011), even though the average wage for high-education labor has gone up significantly – much more rapidly than labor groups of relatively lower education levels. Our results from Figure 4 indicate that the observed strong demand for high-education labor during our sample period is a net outcome of a decreasing price for IT (more IT leads to more high-education labor) and an increasing wage for high-education labor (and thus less demand for high-education labor), with the former's impact being much stronger than that of the latter.

Figure 4: Degree of Complementarity over Time - between IT and High-Education Labor



Discussion and Conclusion

In this study, we try to unravel the debate between the AI and IA perspectives of the impact of IT on human labor. We examine the interaction between IT and human labor in the production process. Our results suggest that both the AI and IA effects exist for today's labor market. The AI effect dominates for low- and middle-education labor while the IA effect dominates for high-education labor. Our results make important theoretical contributions and bear practical implications.

First, prior studies propose that IT and human labor are substitutes in the production process. We argue that the relationship between IT and human labor is more nuanced than what has been conceptualized by prior research. Specifically, we propose that the interaction between IT and human labor (i.e., substitution or complementarity) depends on the employees' education levels. We stratify labor into three groups by their education levels. The results show that, during our study period, IT complements high-education labor, substitutes for low-education labor, and most strikingly, substitutes for middle-education labor. These findings are novel and provide insight in unravelling the debate between the AI and IA perspectives of the IT-labor interaction.

Technology in essence is used to free humans from performing routine and repetitive work and thus allows workers to focus on the creative work. Prior studies have shown that technology advancement favors skilled labor (Autor et al. 2003; Bresnahan et al. 2002). However, our results show that, since late 1990s, IT has become a net substitute for middle-education labor, regardless of which price is changing, IT or labor.

Second, we propose a novel approach to assess the substitution/complementarity between IT and labor, using a combination of two elasticity measures, the AES and the MES, based on a flexible functional form. To our best knowledge, we are the first to use both AES and MES results to offer an intuitive interpretation of the substitution/complementarity relationship between IT and labor. Another advantage of this approach is that it takes into account the output level of the production process, and thus can show a clearer interaction pattern between input factors. Our inclusion of the MES into the interpretation framework is particularly relevant given the drastic price drop for computing equipment versus generally rising wages during the past few decades.

Third, this study provides timely empirical evidence on a topic that is of practical importance for policy making. Through substitution/complementarity with labor, IT is playing an increasingly important role in job destruction and creation. It is critical for practitioners as well as policy makers to better understand how IT interacts with workers — substituting for or complementing part of their work. Our results show that IT not only substitutes for low-education labor force, but also may have replaced jobs that used to belong to the middle-class — the majority of which received college-level education. This may be because that the advancement of technology has changed the nature and responsibilities of many middle-class jobs and require workers to have more technical knowledge and stronger critical thinking skills which cannot be sufficiently offered by college education (Davenport and Kirby 2015; Rampell 2014). Our results also show that the group benefiting the most so far from the massive adoption of IT by the US industries over the years is the highly-educated group — those with graduate or professional degrees. Our findings support the role of higher education in creating new jobs that are complementary to IT investment and thus have rich policy implications.

Overall, our findings suggest that, to fully take advantage of IT and enhance the productivity of labor force, firms need to provide continuous training to their employees to upgrade their skills. Special attention needs to be paid to middle-education workers who used to be complementary to IT but are now falling behind. Therefore, governments should continue their support for higher education to upgrade skills of the labor force to meet the demand of high-education labor driven by technological advancements.

At the same time, governments should heed to and anticipate the potential downsides of a more IT-driven economy, given that IT is likely to displace more and more low- and middle-education labor and thus can potentially lead to unemployment. Resources should also be provided to displace workers due to adoption of new technologies to upgrade their IT skills.

This study is not without limitations. One limitation is that our dataset only covers the years of 1998-2013, and thus we cannot project the future trend of AI and IA. In our framework, the impact of IT is dynamic due to the continuously improving capability of IT. Although we witness the IA effect between IT and high-education labor, it is conceivable that, in the near future, the IA effect may get weaker — there may be a turning point where some of the tasks that used to be performed by these workers will be routinized such that IT and some high-education labor may become substitutes. In other words, we expect that the IA effect may get weaker in the long run while the AI effect may get stronger. Future studies may collect more recent data to verify this unfolding trend between IT and labor.

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