The Effects of Technological Change on Labor Market

1. Introduction

Anxiety about the adverse effect of technological progress on employment and wages has lasted for centuries (Autor, 2014) and is even intensifying in recent years. It is commonly believed that in the period of "Fourth industrial revolution" (World Economic Forum, 2016), a wider range of jobs are exposed to the risk of being substituted by robots. However, it is often neglected that technology also complements workers and creates new jobs. This essay will explain the effects of technological progress on employment, wages and unemployment of high-, middle- and low-skilled labor through analyzing theoretical models and examining empirical evidence.

2. Employment

2.1 Theoretical Model

According to Autor et al. (2003), high-skilled workers typically accomplish non-routine cognitive tasks which require strong capability of analysis, inductive reasoning and communication. Currently, these tasks, which are typically carried out by highly-educated professionals, technicians and managers, cannot be easily computerized. Generally speaking, technology and high-skilled labor are believed to be complements in producing non-routine cognitive services. Therefore, an increase in the supply of high-tech inputs would increase the marginal product of high-skilled workers, thus increasing demand for the high-skilled. This is supported empirically by Michaels et al. (2014) who examine industry-level skill shares of 11 OECD countries over 25 years and find that the growth of demand for high-skilled workers is positively related to the growth of information and communication technology. As is shown in Figure (a), with the demand curve shifting from D to D', in equilibrium, high-skilled workers' employment and wages both increase. The supply curve for high-skilled labor is relatively inelastic in the short and medium term because it takes five to ten years to pursue higher education (Autor, 2014). Thus, the increase in wages would be more significant than the increase in employment.

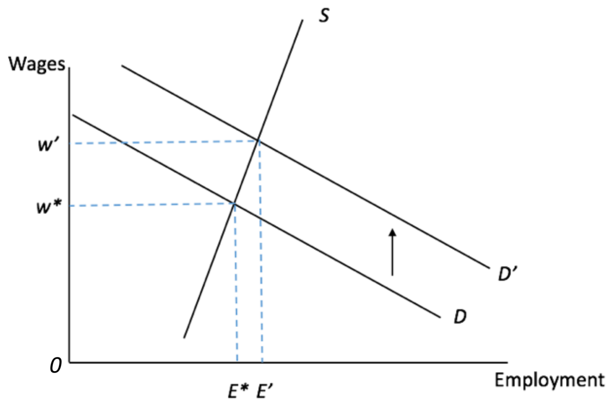


Figure (a)

High-skilled labor may not always be the winner of technological progress since the unprecedented acceleration in capability of artificial intelligence is signifying both massive job displacement and job creation for high-skilled labor in the future. On the one hand, unlike previous waves of automation where machines only served as a tool to improve the productivity of high-skilled workers, the scope of what robots can do has been recently expanding (Brynjolfsson and McAfee, 2011; Ford, 2017). As robots' algorithm becomes increasingly similar to information processing procedure of the human brain, it is reasonable to expect that robots will be able to replace high-skilled labor to accomplish an increasing number of non-routine cognitive tasks, reducing the demand for high-skilled workers. On the other hand, the rise of artificial intelligence requires fundamentally new software, algorithms and related R&D activities, resulting in job creation for high-skilled labor (Nübler, 2016). The relative magnitudes of job creation and job displacement would determine the direction of change in demand, thus determining how employment and wages would change.

Middle skilled labor is characteristic of handling routine tasks such as clerical work, sorting, bookkeeping and repetitive production activities, which can be easily and fully codified and performed by machines (Autor, 2015). This suggests that technology and middle-skilled labor are gross substitutes. As computing power becomes cheaper due to technological progress, profit-maximizing firms are motivated to substitute away from relatively expensive workers toward cost-saving machines, resulting in a lower demand for middle-skilled labor. Kiva Systems used in Amazon warehouse (Ibid) is a typical case in point. In Kiva-operated warehouse, shelves are carried by robots instead of human labor. Regarding the supply of middle-skilled labor, Autor (2014) indicates that it is elastic due to low education and training requirements. Therefore, as is shown in Figure (b), in equilibrium, the decreasing demand (from D to D') for middle-skilled labor leads to a large employment decline and a small wage decline.

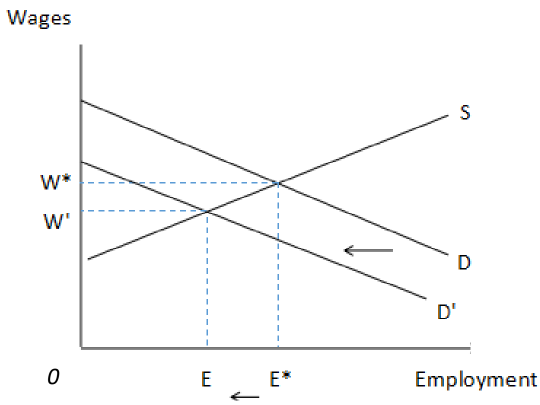


Figure (b)

In low-skilled sector, substitution and complement effects are relatively weak. On the one hand, Goos et al. (2014) find that the majority (61%) of low-skilled occupations are non-routine manual jobs such as waiters, which require language and visual recognition, in-person interactions and situational adaptability. Since the technology that equips robots with these abilities is still immature, currently it is difficult for robots to substitute low-skilled labor (Autor, 2015). On the other hand, low-skilled workers are generally low-paid. Therefore, replacing them is not necessarily cost-saving. Furthermore, to increase output, firms would rather hire more low-wage labor than raise labor's productivity by using expensive labor-complementing machines.

Compared to weak substitution effect and complement effect, income effect plays a relatively significant role in the low-skilled sector. As technological progress boosts productivity, real income increases. According to Sakurai (1997), technology growth can account for 42% of GDP growth, which indicates that technology progress has significantly positive effects on real income. Since the demand for goods and services provided by low-skilled labor is income elastic (Mazzorali and Ragusa, 2013), an increase in income would greatly increase the quantity of those goods and services demanded. Consequently, recall that low-skilled labor is neither substituted nor complemented, producers in low-skilled industry will hire more labor in response to the increasing demand for goods and services.

Similar to middle-skilled labor, supply of low-skilled labor is also elastic (Autor, 2014). In this case, an upward shift of demand for low-skilled labor caused by the income effect leads to a relatively large employment increase and a relatively small wages increase. However, meanwhile, since middle-skilled employment declines, a large proportion of middle-skilled workers would enter low-skilled occupations (Smith, 2013), shifting the supply curve rightwards. As is shown in Figure (c), in equilibrium, the employment of low-skilled workers increases, but their wages may decrease.

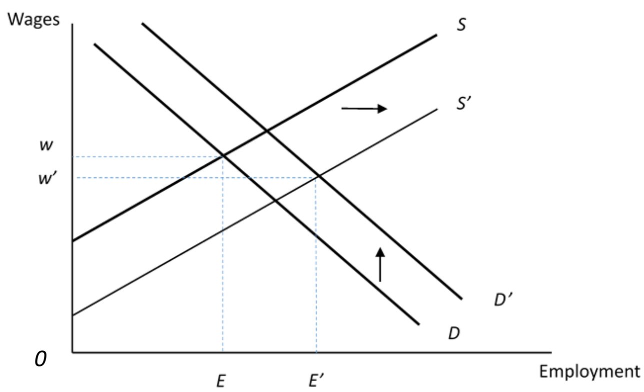
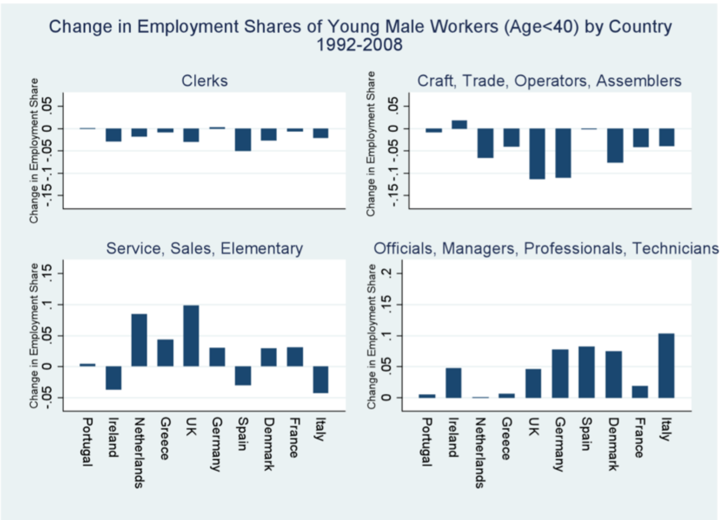


Figure (c)

2.2 Empirical Evidence

The model stated above indicates that technological progress tends to increase the employment of high-skilled and low-skilled labor and decrease the employment of middle-skilled labor. As a result, the employment shares of high- and low-skilled labor would rise while the employment shares of middle-skilled labor would fall. This is exactly what can be observed in America and European countries (Acemoglu and Autor, 2010). The charts below (Figure (d)) show the change in employment share of workers in 10 European countries from 1992 to 2008. This study focuses on workers under age 40 because changes in occupational composition are typically first evident among young workers (Autor and Dorn, 2009). For both genders in these countries, broadly speaking, there is a decline in middle-skilled occupations (clerks, craft, trade, operators and assemblers) and a robust growth in both high-skilled (managers, professionals and technicians) and low-skilled occupations (service and elementary).



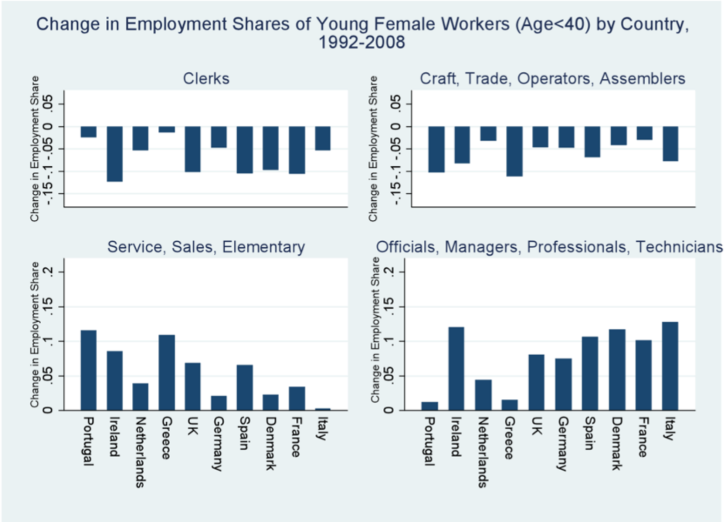


Figure (d)

Counterintuitively, empirical evidence shows that the polarization of employment does not lead to wage polarization. As is shown in Table (1) (Acemoglu and Autor, 2010), the wages of high-skilled labor increased from 1973 to 2009, whereas the wages of low-skilled labor decreased over the same period. The wages of middle-skilled labor were relatively stable. Middle-skilled labor generally saw a slight increase in their hourly wages in the 2000s after experiencing some wage declines from 1973 to 1999. The data are consistent with the logic of the model discussed above and the overall wage decline for low-skilled labor indicates that the wage decline caused by the increase in supply more than offsets the demand-induced wage increase.

B. 100*Log Hourly Wages Relative to 1973 Mean

	1973	1979	1989	1999	2007	2009
All						
Professional, Managerial, Technical	32.8	30.6	37.0	47.4	56.0	57.8
Clerical, Sales	-11.6	-11.9	-13.8	-5.1	-0.8	0.5
Production, Operators	3.0	4.4	-3.8	0.7	5.4	8.9
Service	-40.5	-39.4	-43.7	-32.4	-24.9	-24.3

Table (1)

2.3 Prediction

Such patterns of employment and wages may not continue indefinitely with the accelerating technological progress. Regarding high-skilled labor, technology will disrupt more high-skilled jobs, but many scholars believe that humans are intelligent enough to create more new jobs just as what has been happening since the Industrial Revolution (Wajcman, 2017). Accordingly, the employment and wages of high-skilled labor are unlikely to fall, at least in the near future. As for middle-skilled workers, they will still be the most vulnerable group. Employment of middle-class jobs will decline due to technology improvement and the remaining workers will face stagnant wages. Regarding low-skilled workers, in the near future, their employment still tends to increase and their wages tend to decrease relative to the skilled labor. However, potential technological breakthrough may also arouse significant job displacement in the low-skilled sector.

3. Unemployment

In the standard model analyzed above, labor can choose either to work or not to work. There is nothing to do with unemployment. In this part of analysis, the model is extended by examining the structural unemployment that appears in the short run but disappears in the long run.

Evidence suggests that technological progress causes structural unemployment in the short run (Giffi et al., 2018). According to the formula

$$\frac{\mathrm{U}}{\mathrm{LF}} = \frac{\mathrm{l}}{\mathrm{l} + \mathrm{h}} = \frac{1}{1 + \frac{\mathrm{h}}{\mathrm{l}}}$$

natural rate of unemployment depends on job separation rate and job finding rate. On the one hand, job separation rate rises because an increasing number of workers are substituted by machines. On the other hand, job finding rate decreases because increasingly advanced technology makes it harder for labor to keep pace with technological progress in a relatively short period. These two forces together result in a higher natural unemployment. Regression based on data from 21 industrial countries between 1985 and 2009 demonstrates that technological change substantially increases unemployment within 3 years (Feldmann, 2013).

However, the positive relationship between unemployment and technological change is not significant in the long run (Ibid). The reasons are as follows. Firstly, compared to those in the short run, workers are equipped with more all-round and advanced skills in the long run since they have enough time to receive higher education and more advanced training (Zhu and Li, 2018). These skills strengthen their transferability among industries. Secondly, technological progress leads to industries' skill-biased transformation, continuously creating new jobs. These jobs include advanced R&D activities that machines cannot do, and technology-complementing work such as operating and repairing machines. In other words, labor can be redeployed into these newly-created sectors (Atkinson et al., 2018). So when new technology substitutes workers, higher labor transferability and job creation ability of the economy enable them to transfer among sectors rather than being left unemployed.

4. Conclusion

In conclusion, based on the standard model and empirical evidence, technological progress has caused employment polarization but has not catalyzed wage polarization. It is anticipated that technological innovation will continuously increase employment and wage for high-skilled labor, whereas middle-skilled labor will face even lower employment and a stagnant wage. Regarding low-skilled labor, there will be an increase in employment and a decrease in wages. However, potential technological breakthrough may well change such pattern. Furthermore, technological progress results in structural unemployment in the short run but in the long run, unemployment rate remains steady due to labor transferability and job creation.

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