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Skill Selection and Productivity Growth

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Abstract

This paper aims to investigate the influence of skill selection on productivity gains. To do this, using the productivity of intermediate goods and the average level of technology models, we construct a model in which we show that the implementation of policy based on investment in large technological projects and the selection of the right workers for high-skill tasks left back by automation in technologically advanced firms are the key for the productivity growth. Our model indicates that the size of the firm's project affects the productivity gain. Less investment in technology adoption and creation by small firms generates less productivity. However, the investment in large projects through technology adoption from the leader or innovation via R&D investment enhances both firms' productivity growth and competitiveness and aggrandizes them technologically. The automation process in these firms leaves behind an immense pool of high-skill tasks that need to be filled with a qualified workforce. Thus, selecting the right workers becomes extremely important in productivity growth. The exit from the workplace of low-skill workers with obsolete knowledge will follow the need for high-skill workers with knowledge that suits the new technologies used in the firms making room for machines in repetitive tasks and high-skill workers in high-skill jobs. Besides, we find that high-skill workers increase productivity growth due to the high-skill jobs, which affects the firms' productivity growth. To put it simply, technologically advanced firms, to improve productivity growth, should adopt strategies based on selecting qualified workers that can increase the productivity of high-skill tasks. However, the education system should keep up with the new skill tasks generated by automation in training high-skill workers in the modern work market.

Subject Areas

Economics

Keywords

High-Skill, Productivity Growth, Technologically Advanced Firms, Selection

1. Introduction

The implementation of new technologies by firms to enhance their productivity, efficacy, and competitiveness is changing at an abrupt speed workplace, creating not only an important disparity between the demand and supply of skills but also a significant mismatch between the new technologies and the skill available. The routine tasks done once by humans are starting to be done by machines, leaving low-skilled workers without jobs or struggling to find a job that suits their skills. However, this new knowledge area affects not only the workers but also the firms. The skill disparities affect the motive of firms to adopt new technologies as they have difficulty finding adequate workers to interact with this latter. The lack of adoption of new technologies occludes the production process and slows down both productivity growth and efficiency [1]. Therefore, firms face crucial challenges: how can they stay competitive and enhance productivity growth in this area of new technologies with skill disparity? How can they find the right skilled workers to interact with new technologies?

The literature approached the concept of selection in two different ways. Some papers mentioned the firm's selection: the selection between young, new, old, and incumbent firms [2]-[7]. Others highlight the selection based on skill: the selection between low and high-skill workers [8]-[10]. On the one hand, reference [6] in his work on firm-level selection, contends that two essential factors influence the productivity growth of the United States: new firms entering the market and existing ones. As the number of entering firms decreases and existing companies age, the aggregate productivity growth declines. Thus, the entry of young firms into the market affects better aggregate productivity growth. Likewise, reference [3] also argues that a weak selection power provokes weak productivity growth, especially in SMEs. Exiting firms have lower prices and weak productivity than entering and incumbent ones. However, the productivity advantage of entering firms and young ones on incumbents' ones is slightly higher as young manufacturers, to gain a place in the market and compete, do not charge the same prices as incumbents [2]. On the other hand, reference [8] in his cross-countries selection study, differentiates two types of economies: countries far from and close to the technology frontier[1]. Economies far from the technology leader engage in less selection, relying on incumbent firms and low-skill workers to maximize investment. However, countries closer to the technology-leading select younger, dynamic firms and high-skill workers since the economies start investing in their R&D to create new knowledge to improve productivity growth. Likewise, less productive firms survive in the market using credit strategies to finance technology adoption and other firm costs. These strategies reduce their power of innovation and their productivity. At the same time, less access to credit decreases costs and enlarges the firm, which leads to more innovation and productivity growth [10].

[1]See reference [8] [11]-[14] for better understanding of the technology frontier concept.

One of the earlier works on skill selection and growth was the one of reference [8] combined with the one of reference [15]. Reference [8], based on reference [15]' essay, develops an endogenous model in which an economy has three main characteristics: (i) managers' skill (high or low skill); (ii) investment limit due to credit constraints; (iii) and innovation and adoption of technologies from technology leaders. In their model, they take two different economies with two policies: Innovation and adoption of technology. They show that a country closer to the frontier invests in innovative activities to improve productivity growth. It implements thus a strategy based on innovation in which the selection of high-skill entrepreneurs becomes a priority. As innovation activities intensify, retaining low-skill entrepreneurs is more expensive and less likely to happen in equilibrium. Firms maintain low-skill entrepreneurs in an economy where they invest in technology adoption policies to increase productivity. Their work emphasized cross-countries.

In our paper, we investigate the influence of skill selection on productivity gains. To do this, by adapting at a technologically advanced firm level, the productivity of intermediate goods and the average level of technology models also used by reference [8] in cross-countries comparison, we develop a model in which the implementation of policy based on investment on large technological projects and the selection of right workers for high-skill tasks left back by automation in technologically advanced firms is the key to enhance the productivity gain. In our model, unlike that of reference [8] and other studies that precede us, the type of technological activities (innovation or adoption) does not matter. The foremost factor is the intense use of advanced technologies in the production process. We consider the existence of a firm leader in technology use: highly advanced in new technologies use firm. We start from the assumption that firms invest in advanced technologies either by innovating or adopting technologies from the leader firm or other firms to improve productivity growth and competitiveness. In our model, the size of the project firms engage in is extremely important to productivity growth. However, contrary to the model of reference [8], we mean by the size of the project, the limited investment in technology, and the large one. Firms investing more in technology are technologically advanced (large). However, we classify firms that invest less in technological activities as small firms and far from the leader. Therefore, we suppose that the more the firm invests in technologies, the more it enlarges its size and becomes technologically advanced. Accordingly, becoming technologically advanced, the firm through automation generates a vast pool of high-skill tasks that cause manufacturers to look for a qualified workforce. However, does a high-skill worker mean the right worker for the job available? A strong supply of qualified workers in the employment market could not necessarily indicate the right workforce in demand for high-skill tasks left behind by the automation system. Skill selection becomes essential to increase productivity growth. As weak selection leads to declining productivity growth, firms should be rigorous and meticulous in their selection [2] [3].

As we mentioned above, many theoretical and empirical works approached the link between selection and productivity gain [2]-[7]. However, most of this literature was about firm selection (firm entry and exit). Only a few numbers of papers analyze the effect of skill selection on firms' productivity growth [8]-[10]. For instance, while reference [8] analyzes the influence of skill selection on growth at the cross-section level, reference [9] investigates the effect of adequate farmers' selection on aggregate agricultural productivity. Moreover, reference [10], using a model of innovation and growth, analyzes the relationship between credit and productivity growth considering the role of selection. However, in our research on the subject, we noticed that the existing literature hardly examined the influence of the right workers' selection for the task left behind by automation in technologically advanced firms' productivity gain. Hence the interest in our research.

The structure of the rest of the paper is as follows: Section 2 summarizes the literature review. In section 3, by using the productivity of intermediate goods and the average level of technology models used by reference [8], we show that selection plays a predominant role in productivity growth. We conclude our paper with section 4.

2. Literature Review

We divide the literature related to selection and productivity growth into two categories: The firm selection [2]-[6] and the skill selection [8]-[10]. Reference [2], using establishment-level data for producers of eleven manufacturing products over the selected years (1977, 1982, 1987, 1992, and 1997), investigates the nature of selection and productivity growth in industries. They observe the producer-level quantities and prices separately. They find that aged firms having lower price policies find it difficult to increase productivity compared to younger and incumbent firms. Furthermore, they conclude that young and entering firms physically enhance their productivity growth more than incumbent ones as they charge lower prices to gain a place in the market and compete with the older ones. Reference [3], using two firm-level datasets (COMPUSTAT and AMADEUS) analyzes the patterns of market selection in manufacturing industries of France, Germany, the UK, and the USA over the period 2000-2007. They find a weak relationship between productivity and the power of selection forces in all four countries. Besides, their findings demonstrate that the selection affects more SMEs. Accordingly, reference [4], using a rich cross-country firm-level dataset, examines the influence of selection and market reallocation on aggregate productivity growth. Their results suggest that selection and market reallocation are decisive in multinational production aggregate productivity. Besides, reference [5] investigates the impact of firm selection on plant-level productivity. Findings from establishment-level census data from Ethiopia for the 2000-2010 period indicate that firm selection is a crucial driver of the cities' aggregate productivity growth. The study further suggests that when the producers' transport costs are controlled in a competitive market, less productive firms are likely to quit the market than more productive ones. Accordingly, reference [6], through the US nonfarm business sector dataset over the 1996-2012 period, observes that the influence of entering and young on the US aggregate productivity growth is more substantial than old and incumbents' ones.

At the skill selection level, reference [8] analyzes an economy in which firms use both innovation and technology adoption regarding their distance from the technology leader to enhance productivity growth. They show that as a country moves closer to the frontier, it implements a strategy based on innovation in which the selection of high-skill entrepreneurs and young firms becomes essential to enhance productivity growth. On the other hand, firms in countries far from the leading country in technology engage in strategies based on large investments, long-term relationships, and less selection. In another study conducted at the skill selection level, reference [9] was observed from household-level panel data from China, which showed the effect of the selection of adequate farmers on aggregate agricultural productivity. They find that friction in the land and financial markets leads to poor distribution of resources among farmers on the one hand and affects the selection of farmers on the other. This friction, in turn, reduces aggregate productivity growth. Besides, reference [10], using a model of innovation and growth analyzes the relationship between credit and productivity growth considering the role of selection. He noticed that the increase in firms' productivity relies on both the selection strength and the size of the firms. As large firms conduct more innovation activities, the selection of high-skill workers becomes the priority to increase productivity growth.

3. The Model Frames

We investigate the influence of skill selection on productivity gains. To do this, by adapting at a technologically advanced firm level, the productivity of intermediate goods and the average level of technology models also used by reference [8] in cross-countries comparison, we construct a model in which the selection of the right workers and the implementation of policy based on investment on large projects are the principal keys for the productivity growth. Right workers signify workers who have hard-to-find skills that manufacturers need in firms to fill high-skill labor shortages left behind by automation. In effect, with automation in the workplace, certain tasks have become obsolete. Some workers have had to change careers to move towards training that requires high skills in managing new technologies. Others have updated their knowledge to better match the new tasks brought about by automation. Therefore, the labor market currently contains a considerable number of qualified workers. However, having high-skill workers in the market does not necessarily imply having the right workers for the tasks of need. Since some of the tasks requiring high skills left behind by automation are even saturated, according to reference [1], manufacturers in technologically advanced firms need skilled workers who have hard-to-find skills in specific areas, not in all areas. Hence, they need to select the right workers, not simply high-skill workers.

Paralleling Reference [8]' model, we assume that productivity growth is a function of the workers' skills and the firm's project size. Generally, there are two types of workers: High-skill and low-skill workers. In our model, we assume that firms engage either in small or large projects. We mean small projects, the projects based on less investment in the creation and adoption of technologies. Likewise, we suggest that large projects lead firms into more innovation or technology imitation. Furthermore, we assume that the selection of highly skilled workers becomes essential when the firm becomes larger and more technologically advanced. To put it simply, our model considers technologically advanced firms[2] in which manufacturers need both qualified and unqualified employees. Unqualified workers do routine and physical tasks, and highly skilled workers are more suitable for new tasks left behind by automation. However, we assume that when automation intensifies, all repetitive and routine tasks done before by low-skill workers should be done by machines. Machines will increase the productivity of routine tasks, leaving the high-skill jobs' productivity to high-skill workers to improve. Overall, we base our model on two essential features: (i) Technologically advanced firms with intense automation (policy based on investment in large projects) and (ii) The selection of the right workers for high-skill tasks. That leads to the crucial assumption of our model: *The more the firms are advanced in technology, the more they should select high-skill workers for high-skill tasks left behind by automation to improve productivity growth.* In our models, we adapt at the technologically advanced firm level, the productivity of intermediate goods, and the average level of technology models also used by reference [8] in their endogenous growth model. To do this, we first consider the aggregate production function:

$$y_t = \frac{1}{\alpha} N_t^{1-\alpha} \left(\int_0^1 \left(A_t(v) \right)^{1-\alpha} x_t(v)^{\alpha} \, \mathrm{d}v \right) \tag{1}$$

In this function, $x_t(v)$ denotes the flow of intermediate good v used in final good production, N_t is the number of production workers at time t, and $\alpha \in (0,1)$.

$A_t(v)$ is the productivity in sector v at time t and is expressed as:

$$A_t(v) = s_t(v)\left(\eta \bar{A}_{t-1} + \gamma_t(v) A_{t-1} \right) \tag{2}$$

where $s_t(v) \in (\sigma, 1)$ represents the size of the project, $s_t(v) = \sigma < 1$ for a small project, and $s_t(v) = 1$ for a large project. $\bar{A}_{t-1}$ denotes the state of the leading technology firm in the previous period. We suppose that the leader firm is the firm that reaches the threshold in the use of technology in the production process. However, some firms use the same technology to have the same productivity $A_t(v)$ either by creating their technology or adopting this latter from the leader.

[2]Note that in our study, we assume technologically advanced firms to be firms that create their own technology. A firm can adopt or imitate a technology from the leader but still be a technologically advanced firm as it uses intensely these adopted or imitated technologies in its production process.

A_{t-1} represents the productivity growth of innovation in reference [8]'model. In our model, we denote A_{t-1} as the productivity growth due to the high-skill tasks in a technologically advanced firm whose performance depends on the skill $\gamma_t(v)$ of workers. We do this for a reason. Complex problem-solving, critical thinking, creativity and design, judgment and decision-making, cognitive flexibility, adaptation to change, digital skills, and so on are innovative skills [16] [17], and at the same time, represent the high-skill tasks left behind by automation in technologically advanced firms.

Assuming that in technologically advanced firms, the low-skill do not have the skills needed to influence considerably output, we equate their skill $\gamma_t(v)$ to zero: $\gamma_t(v)=0$. Assuming $\gamma_t(v)=0$, amounts to saying that skill in technologically advanced firms is more important if the worker is a high-skill one. This assumption is common in the literature. For instance, reference [18], in his seminal work highlights the importance of high-skill workers by assuming that only the manager skill (the skill of the most qualified agent in the firm) matters in the production process. By assuming $\gamma_t(v)=0$, $A_t(v)$ becomes:

$$A_t(v)=s_t(v)\eta\bar{A}_{t-1} \tag{3}$$

From Equation (3), with the assumption that $\gamma_t(v)=0$, the productivity growth depends only on the size of the project and the state of leading technology in the previous period when. Thus, Equation (3) partially confirms the monopoly power of the leading firm that uses the most productive technology that other firms do not have access to to enhance productivity growth, in line with reference [8]. The equation also implies that less the size of the project is, less the productivity increases. Therefore, small firms need to enlarge the size of their project by investing more in technology through the adoption of technology from the leader to improve productivity growth. Once they start investing in a larger project and become advanced technologically, the skill $\gamma_t(v)$ in demand in the market should become $\gamma_t(v)>0$. That is, as the firm's project becomes large, low-skill workers ($\gamma_t(v)=0$) should become useless in the enhancement of productivity growth and firms are engaging in the search for more competent and qualified workers capable of filling the high-skill tasks left behind by automation. Our productivity function $A_t(v)$ becomes:

$$A_t(v)=s_t(v)\left(\eta\bar{A}_{t-1}+\gamma_t(v)A_{t-1}\right) \tag{4}$$

The high-skill task productivity A_{t-1} left back by the automation in the technologically advanced firm is an essential part of the productivity growth $A_t(v)$. The more the skill level γ_t of workers moves away from 0, the higher the productivity growth A_{t-1} due to the high-skill tasks, which affects the average productivity growth $A_t(v)$. This feature introduces the assumption that firms, to stimulate productivity growth, need to increase the productivity of high-skill tasks. Accordingly, to enhance the productivity of high-skill tasks, firms need to implement a vital policy based on the selection of highly skilled workers for new jobs and skills created by the automation system.

Second, by dividing the average level of technology A_t in the firm at time t

by A_{t-1} where $A_t = \int_0^1 A_t(v)\mathrm{d}v$ we obtain the following equations:

$$\frac{A_t}{A_{t-1}} \equiv \frac{\int_0^1 A_t(v)\mathrm{d}v}{A_{t-1}} \tag{5}$$

$$\frac{A_t}{A_{t-1}} = \frac{\int_0^1 \left(s_t(v)\left(\eta \bar{A}_{t-1} + \gamma_t(v) A_{t-1}\right)\right)\mathrm{d}v}{A_{t-1}} \tag{6}$$

$$\frac{A_t}{A_{t-1}} = \int_0^1 s_t(v)\left(\eta \frac{\bar{A}_{t-1}}{A_{t-1}} + \gamma_t(v)\right)\mathrm{d}v \tag{7}$$

$\frac{\bar{A}_{t-1}}{A_{t-1}}$ denotes the technological level between other firms and the technology leader firms.

The firms in which the automation is not intensive, it is to say that firms that are not technologically advanced see their $\eta \frac{\bar{A}_{t-1}}{A_{t-1}}$ term large. However, when $\eta \frac{\bar{A}_{t-1}}{A_{t-1}}$ term is closer to 1, the firm is an intensive user of new technologies in the production process reference [8]. This leads us to the following equation:

$$\begin{cases} \frac{A_t}{A_{t-1}} = \int_0^1 s_t(v)\gamma_t(v)\mathrm{d}v & \text{if } \eta \frac{\bar{A}_{t-1}}{A_{t-1}} = 1 \\ \frac{A_t}{A_{t-1}} = \int_0^1 s_t(v)\left(\eta \frac{\bar{A}_{t-1}}{A_{t-1}} + \gamma_t(v)\right)\mathrm{d}v & \text{if } \eta \frac{\bar{A}_{t-1}}{A_{t-1}} \cong 1 \end{cases} \tag{8}$$

$\frac{\bar{A}_{t-1}}{A_{t-1}} = 1$ depicts the technology leader firm and $\frac{\bar{A}_{t-1}}{A_{t-1}} \cong 1$ for the others technologically advanced firms. Equation (8) implies that the more the firm is advanced in the use of new technologies in production, the more skill selection is important to productivity growth. Widely speaking, technologically advanced firms, to stimulate productivity growth, adopt strategies based on selecting qualified workers that can increase the productivity of high-skill tasks that constitute an important part of the firms' productivity gain.

Our model observes that productivity growth is a function of the size of the firm's project. Small firms investing less in the adoption and creation of technologies find it difficult to increase productivity growth. Therefore, firms need to enlarge their project size by either investing in technology through technology adoption from the leader or creating their technology via R&D investment to improve productivity growth. Once they start investing in a larger project and become advanced technologically, the skill $\gamma_t(v)$ in demand in the market becomes $\gamma_t(v) > 0$. That is, as the firm's project becomes large, low-skill workers ($\gamma_t(v) = 0$) become useless in the enhancement of productivity growth, and firms go into the search for more competent and qualified workers capable of filling the high-skill tasks left behind by automation. The need for high-skill workers with new knowledge: knowledge that suits the new technologies should force low-skill workers with obsolete knowledge to leave the workplace, making room for machines in repetitive tasks and high-skill workers for high-skill jobs. In technologically advanced workplaces, as AIs perform routine and physical tasks, the remainder of tasks left behind by automation will be done by high-skill workers. Thus, the selection will target mainly employees with high, cognitive, digital, and coding skills. Therefore, the level of education and training should evolve in parallel with the high-skill tasks in automated firms. That means universities and other educational establishments should amplify and intensify the training and teaching of high skills derived from new jobs. The implementation of such a policy will lead to the possibility of having more high-skill workers who have graduated from universities and are employed by businesses.

4. Conclusions

In our paper, we investigate the influence of skill selection on productivity gains. To do this, by adapting at a technologically advanced firm level, the productivity of intermediate goods and the average level of technology models, we develop a model in which we show that the implementation of policy based on investment in large technological projects and the selection of right workers for high-skill tasks left back by automation in technologically advanced firms are the key to enhance the productivity gain.

Our model indicates that the size of the firm's project affects the productivity gain. Small firms investing less in the adoption and creation of technologies find it difficult to increase productivity growth. Therefore, firms need to enlarge their project size by either investing in technology through technology adoption from the leader or creating their technology via R&D investment to improve productivity growth. Becoming larger, low-skill workers become useless in productivity improvement since automation leaves behind an immense pool of high-skill tasks that need to be filled with a qualified workforce. For instance, only high-skill manager can suggest great management techniques and bring new ways to organize the production to increase que total factor productivity (TFP). The need for high-skill workers with new knowledge: knowledge that suits the new technologies may force low-skill workers with obsolete knowledge to leave the workplace, making room for machines in repetitive tasks and high-skill workers for high-skill jobs. Nevertheless, the supply of qualified workers is limited, and as there are easy-to-find and hard-to-find skills in the labor market, finding high-skill workers does not necessarily indicate finding the right worker for a task required by high automation. Widely speaking, in technologically advanced firms, one thing is to have a supply of qualified workers on the employment market, and another is to analyze and select those who meet precisely the criteria of high-skill tasks left behind by automation. Therefore, the selection of the right workers is extremely important to enhancing productivity growth. Manufacturers should select meticulously highly skilled workers for high-skill tasks whose productivity directly affects firms' productivity growth. To do that successfully, they should collaborate with universities or other educational institutes by investing in hard-to-find skill training areas of universities, following bright students from these fields and employing them after they graduate.

Besides, we find that high-skill workers increase productivity growth due to the high-skill jobs, which affects the firms' productivity growth. To put it simply, technologically advanced firms, to stimulate productivity growth, should adopt strategies based on selecting qualified workers that can increase the productivity of high-skill tasks constituting a significant part of the firms' productivity growth. The selection targets workers with skills like creativity, adaptation, decision-making, complex problem-solving, critical thinking, creativity, people management, cognitive flexibility, and so on, the level of education and training should evolve in parallel with the high-skill task in automated firms. That means universities and other educational establishments should amplify and intensify the training and teaching of high skills derived from new jobs. The implementation of such a policy will lead to the possibility of having more high-skill workers, especially hard-to-find skilled workers who graduated from universities and are employed by businesses.

Our study has some limitations that are important to highlight. First, the model we developed in the study is a theoretical one. In future studies, the results may be more inclusive if there are high-skilled data to conduct empirical studies on the topic to strengthen our theoretical model findings further. Second, Real-world scenarios often involve upskilling and reskilling initiatives during the automation process. Not all low-skill jobs will be replaced by machines in real-world scenarios. Therefore, assuming that all low-skill workers become obsolete in technologically advanced firms is limited.

Conflicts of Interest

The author declares no conflicts of interest.

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