A Note on Human Capital, the Division of Labor, and Artificial Intelligence

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Abstract

This short paper considers the effects of artificial intelligence (AI) tools on the division of labor across tasks. Following Becker and Murphy (1992) I posit a "team" with each team member being assigned to a task. The division of labor (that is, the number of specialized tasks) is here limited not only by the extent of the market, but by coordination costs. Coordination costs stem from the need for knowledge in multiple tasks, as well as from monitoring and punishing shirking and other malfeasance. The introduction of AI in this model helps the coordination of the team and fully or partially substitute for human "generalist" knowledge. This in turn can make specialization wider, resulting in a greater number of specialized fields. The introduction of AI technologies also increases the return to fully general knowledge (i.e. education).

1 Introduction

There is widespread speculation about which tasks certain types of artificial intelligence (AI) will automatize so that jobs and skills related to these tasks become "obsolete". In the last several decades technological change has been mostly skill-biased, meaning it has increased demand for high-skilled relative to low-skilled labor. The spread of AI could be different, as several commentators hope or fear that AI might soon be able to do what a lawyer or a general practitioner doctor is able to do. The implicit assumption is that the introduction of AI into production

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processes may not be skill-biased, or may be skill-biased in favor of low, not in favor of high skills. Yet, it is reasonable to assume that highly educated individuals will be better able to work with AI and AI-generated input than lower educated ones. Thus we also have an argument for AI driven technological change to favor the high-skilled. This paper takes a "middle way" approach. I show that AI increases high-skilled specialization but also decreases, to an extent, the demand for high-skilled "generalists". These high-skilled generalists then may be able to retrain themselves as high-skilled specialists. The stock of general knowledge would, in turn, grow due to the greater number of specialists expanding the frontier of human knowledge. Demand for low-skilled jobs may not initially change, but over the longer run it might, depending on the elasticity of substitution between high- and low-skilled labor. This question is, however, beyond the scope of the present paper. The main insight I build on can be found in a number of previous articles, including Becker and Murphy (1992), Lazear (2005), Autor and Handel (2013), as well as in Deming (2017). I stipulate an economy, sector or firm (it does not really matter which from an analytical perspective) which, following Becker and Murphy and the literature that followed, I will call a "team" that produces a homogenous output and where the production process can be divided into different specialized "tasks". Division of labor among team members are beneficial due to increasing returns from investing in specialized human capital. My main departure from Becker and Murphy, and this is similar to how Lazear tackles the problem, is to assume that attached to the team are individuals (or at least one individual) who do not specialize, rather, they are responsible for coordinating the efforts of team members. Such generalists might be entrepreneurs, as in Lazear, or they might be "general practitioners", such as family doctors. Throughout the paper I focus on generalists mainly of the latter type, for reasons I will explore later. Generalists need to absorb not only completely general knowledge but also some of the knowledge that is specific to all of the different tasks. The need to coordinate the production process imposes a limit to the division of labor. To see why this is important, consider the problem of a patient in the healthcare sector.The patient may have a number of health symptoms, for which different specialists may propose different diagnoses, but all of these diagnoses might be "biased" due to the highly specific nature of the specialists' knowledge. How does the patient know who to consult with and what examinations she should be subjected to? Clearly, highly specialized doctors may not be able to direct here in this manner. There comes the general practitioner into the picture who essentially coordinates the process of diagnosing and then treating the patient. Of course, specialists also need to know bits of knowledge related to other fields, but from this we abstract away and assume that only generalists accumulate multiple types of specialized knowledge, while everyone's productivity is enhanced by general knowledge that is assumed to be equally useful in all tasks.My basic results would not be qualitatively different if we assumed multiple specializations in general. My model has some similarity to that of Deming (2017) as he also emphasizes coordination costs as a limit to the division of labor. In Deming's framework, coordination costs can be lowered by acquiring better social skills; i.e. individuals who are socially more adept can better coordinate and trade across each other. This paper does not consider this otherwise important aspect of coordination, instead I concentrate on the kind of coordination where artificial intelligence tools are more likely of help.

2 The Model

A general result I derive, after Becker and Murphy (my model is identical to theirs up to equation (4)), is that the division of labor is limited by the cost of coordination. Here I endogenize coordination costs in the following way: let us start with n number of individuals (specialists) in the team. For now I assume that $n \leq N$, where N is the number of individuals in the whole "economy", that is, in this model the division of labor is *not* limited by the extent of the market. The production function can be written $Y = AH \min\{x_1 t_1; ...; x_n t_n\}$, meaning that tasks are perfect complements and each task is "equally important". A is not exogenous, rather it depends on the ability of one or more "generalists" to coordinate production between the different specialists (I will discuss this further later). The production of task s depends on the time allocated to the task $T(s)$ as well as the productivity of each hour $E(s)$. The productivity of time can be characterized by the following equation:

$$E(s) = dH^{\gamma} {T_h}^{\theta}(s), \tag{1}$$

where θ determines the marginal productivity of T_h, the time spent on acquiring task-specific skills. General knowledge H increases the productivity of each specialized team member, with $\gamma > 0$. The total time devoted to the sth skill is $T(s)$, so that

$$T_h(s) + T_w(s) = T(s). \tag{2}$$

Time is allocated between working and investment in specialized knowledge, which leads to

$$Y(s) = A(\theta) H^{\gamma} T(s)^{1+\theta} \tag{3}$$

, where where γ and θ are parameters and $A = d\theta^{\theta}('+\theta)^{-(1+\theta)}$. If each team member allocates one unit of working time uniformly across $1/n$ tasks, then $T(s)W = T(s)(1/n) = 1$. Then

$$Y = AH^{\gamma} n^{1+\theta} \tag{4}$$

. Let us now turn to the problem of generalists. Each generalist has to learn a certain amount in each specialty in order to be an effective coordinator. So, for instance, a general medical practitioner must know a certain amount about cancer, cardiovascular diseases, and so on. As more people become specialists, the knowledge needed for generalists increases, which then increases the cost of training generalists, which in turn puts a limit on the number of specialists. Thus there is a clear tradeoff in increasing the number of specialists: as their number increases, there is an increase in production efficiency due to increasing returns to specialization, however, productivity may also decrease because coordination becomes more difficult as generalists need to absorb a greater amount of knowledge. Assume now, without a substantial loss of generality, that there is only one generalist who coordinates the team, and the number of tasks are equal to the number of specialists (n). The former assumption can be justified by the fact that total market size (N) is fixed, so greater specialization would not need to lead to a greater number of general practitioners. To put it somewhat differently, output per worker does not increase with the number of generalists. As for the latter assumption, it means that in essence, for each new specialist a new task is created (which probably would have been a subfield within a field before). Now suppose that the cost of absorbing new knowledge is the same across specialties. Then the amount of knowledge the generalist will have in each areas will be given as T_g/n, where T_g is the time available to the generalist.That is, a more extensive specialization has, apart from its positive effects, a negative effect of decreasing the amount of productive knowledge the generalist has. Let A be written, without a loss of generality, as T_g/n, and T_g be normalized to 1, so that the production function per team member can be given as

$$y = H^{\gamma} n^{\theta-1}. \tag{5}$$

I assume that $\theta > 1$, that is, there are increasing returns associated with greater specialization. Here I will introduce (following Becker and Murphy (1992)) an additional cost of increasing n, which takes the form $c_n n^{\beta}$, where $\beta \geq 1$. This can be interpreted as another type of cost of coordinating specialization, beyond the fact that the generalist coordinator needs to familiarize herself in each specialty. For instance, the greater the number of team members, the higher the risk of shirking or other malfeasance by each team member and thus this cost can be interpreted as the cost of monitoring and punishing opportunistic behavior. The first-order condition with respect to n is

$$(\theta - 1)H^{\gamma} n^{\theta-2} = \beta c_n n^{\beta-1}. \tag{6}$$

For n we obtain

$$n = \Big[\frac{(\theta - 1)H^{\gamma}}{\beta c_n}\Big]^{\frac{1}{\beta-\theta+1}}. \tag{7}$$

We can also solve the model for the optimal H, that is, the amount of general human capital accumulated by each individual. Let the cost of acquiring human capital be $c_H H^{\phi}$.

We obtain

$$H = \left[\frac{\gamma n^{\theta-2}}{\phi c_H}\right]^{\frac{1}{\phi-\gamma}}. \tag{8}$$

Substituting the two first-order conditions into each other we obtain

$$n^* = \left[\frac{(\theta-1)\left[\frac{\gamma}{\phi c_H}\right]^{\frac{\gamma}{\phi-\gamma}}}{\beta c_n}\right]^{\frac{\phi-\gamma}{(\phi-\gamma)(\beta-\theta+1)-(\theta-2)\gamma}} \tag{9}$$

and

$$H^* = \left[\frac{\gamma\left[\frac{(\theta-1)\left[\frac{\gamma}{\phi c_H}\right]^{\frac{\gamma}{\phi-\gamma}}}{\beta c_n}\right]^{\frac{(\theta-2)(\phi-\gamma)}{(\phi-\gamma)(\beta-\theta+1)-(\theta-2)\gamma}}}{\phi c_H}\right]^{\frac{1}{\phi-\gamma}}. \tag{10}$$

The incentive to invest in completely general knowledge increases in the number of specialists and decreases in θ.

2.1 Introducing artificial intelligence into the model

In this section I introduce the basic characteristics of artificial intelligence (AI) into my model. The assumption I make is that particular forms of artificial intelligence, such as large language models, are especially good at synthesizing knowledge, knowledge that otherwise might be dispersed across many different individuals with specialized knowledge. A prime example of that are OpenAI's large language models ChatGPT and GPT-4 which serve as some form of conveyors of general knowledge, but can also direct us to many types of specialized knowledge. These language models are trained to understand as well as generate texts in a human-like fashion (Teubner et al, 2023). A key feature of these models is that they can typically learn much faster than humans about a particular specialized field, even if it is a highly imperfect "student". There is, in essence, much less of a quantity-quality tradeoff in terms of the specialized knowledge acquired in a system powered by AI than in a system using human generalists. Even though an AI "agent" might also have a limited amount of time, it is relatively easy to reproduce AI once the technology to do so is available. Here, for the sake of simplicity, I assume there is no quantity-quality tradeoff at all; i.e. the AI tools can aggregate knowledge form multiple specialized fields without hitting a time constraint. Therefore, as the number of specialized fields grows, AIs can absorb new specialized knowledge at no additional cost. In essence, AI allows for deeper specialization. Meanwhile, we can also see that both the stock of general knowledge and the ease at which general knowledge can be acquired increases with the introduction of AI, and this in turn leads to team members accumulating more (and not less, as some commentators suggest) of general human capital. This in turn further increases the return to invest in task-specific human capital, contributing to a "virtuous circle". In the final equilibrium, we are left with a greater number of team members who have higher levels of general and specific human capital.

Formally, under AI coordination, output per team member is modified to

$$y = H^{\gamma} n^{\theta}, \tag{11}$$

so that the first order condition modifies to

$$\theta H^{\gamma} n^{\theta-1} = \beta c_n n^{\beta-1}, \tag{12}$$

yielding

$$n = \left[\frac{\theta H^{\gamma}}{\beta c_n}\right]^{\frac{1}{\beta-\theta}}. \tag{13}$$

For H we obtain

$$H = \left[\frac{\gamma A n^{\theta-1}}{\phi c_H}\right]^{\frac{1}{\phi-\gamma}}. \tag{14}$$

Substituting the two first-order conditions into each other we obtain

$$n^{**} = \left[\frac{\theta\left[\frac{\gamma}{\phi c_H}\right]^{\frac{\gamma}{\phi-\gamma}}}{\beta c_n}\right]^{\frac{\phi-\gamma}{(\phi-\gamma)(\beta-\theta)-(\theta-1)\gamma}} \tag{15}$$

and

$$H^{**} = \left[\frac{\gamma\left[\frac{\theta\left[\frac{\gamma}{\phi c_H}\right]^{\frac{\gamma}{\phi-\gamma}}}{\beta c_n}\right]^{\frac{(\theta-1)(\phi-\gamma)}{(\phi-\gamma)(\beta-\theta)-(\theta-1)\gamma}}}{\phi c_H}\right]^{\frac{1}{\phi-\gamma}}. \tag{16}$$

Comparing what we obtained for n^* and n^{**} we can clearly see that AI induces greater and deeper specialization (that is, $n^{**} > n^*$) as

$$\left[\frac{\theta\left[\frac{\gamma}{\phi c_H}\right]^{\frac{\gamma}{\phi-\gamma}}}{\beta c_n}\right]^{\frac{\phi-\gamma}{(\phi-\gamma)(\beta-\theta)-(\theta-1)\gamma}} > \left[\frac{(\theta-1)\left[\frac{\gamma}{\phi c_H}\right]^{\frac{\gamma}{\phi-\gamma}}}{\beta c_n}\right]^{\frac{\phi-\gamma}{(\phi-\gamma)(\beta-\theta+1)-(\theta-2)\gamma}}. \tag{17}$$

Furthermore, we can also compare H^* with H^{**} and obtain that $H^{**} > H^*$, or

$$\left[\frac{\gamma\left[\frac{\theta\left[\frac{\gamma}{\phi c_H}\right]^{\frac{\gamma}{\phi-\gamma}}}{\beta c_n}\right]^{\frac{(\theta-1)(\phi-\gamma)}{(\phi-\gamma)(\beta-\theta)-(\theta-1)\gamma}}}{\phi c_H}\right]^{\frac{1}{\phi-\gamma}} > \left[\frac{\gamma\left[\frac{(\theta-1)\left[\frac{\gamma}{\phi c_H}\right]^{\frac{\gamma}{\phi-\gamma}}}{\beta c_n}\right]^{\frac{(\theta-2)(\phi-\gamma)}{(\phi-\gamma)(\beta-\theta+1)-(\theta-2)\gamma}}}{\phi c_H}\right]^{\frac{1}{\phi-\gamma}}. \tag{18}$$

The introduction of AI increases the number of specialized workers and therefore also the breadth of specialization and decreases the number of workers in the team who are assigned to be generalists. At the same time, the amount of general knowledge per team member, also increases, as it is an increasing function of n. In other words, AI tools increase the marginal product of general education ($\gamma H^{\gamma-1}n^{\theta} > \gamma H^{\gamma-1}n^{\theta-1}$). It follows trivially that output also increases with the introduction of AI technology. In my framework, therefore, AI is not a substitute, but a complement to both specialized and general knowledge. This model, therefore, seems to recommend a more "optimistic" attitude to advances in artificial intelligence. However, when coordination is done by "general practitioners", or in other words, a group of workers who are specialized to be generalists, there are short-term adjustment costs of the introduction of AI technologies given that these workers would have to respecialize. When coordination is done by all workers (specialists) learning some of the knowledge associated with other specialized tasks, this problem does not occur. In Lazear's theory of specialists and generalists, generalists are the entrepreneurs tasked with coordinating teamwork. In contrast, the generalists in my model are notably not entrepreneurs. It is perhaps quite unlikely that AI would ever becomes adept at "mimicking" entrepreneurial talent, given that what makes a good entrepreneur might be too "subjective" and involve sufficient amount of "soft skills" so that humans would always be better entrepreneurs than machines (see also Deming (2017) for a model of coordination where soft skills are important).

2.2 The extent of the market

Previously I assumed that $N > n$ but naturally, for a fixed N, it may not hold. That is, after a certain point, the division of labor, as Adam Smith emphasized, will be constrained by the extent of the market. Then n^* can be written in a more general form as

$$\min\left\{\left[\frac{(\theta-1)\left[\frac{\gamma}{\phi c_H}\right]^{\frac{\gamma}{\phi-\gamma}}}{\beta c_n}\right]^{\frac{\phi-\gamma}{(\phi-\gamma)(\beta-\theta+1)-(\theta-2)\gamma}}; N\right\}, \tag{19}$$

while n^{**} can be written as

$$\min\left\{\left[\frac{\theta\left[\frac{\gamma}{\phi c_H}\right]^{\frac{\gamma}{\phi-\gamma}}}{\beta c_n}\right]^{\frac{\phi-\gamma}{(\phi-\gamma)(\beta-\theta)-(\theta-1)\gamma}};N\right\}. \tag{20}$$

If N is sufficiently small so that $n^* = N$, then $n^{**} = N$ as well. That is, in a small market, it may not be worthwhile to introduce artificial intelligence tools into the production process. If $n^* < N < \left[\frac{\theta\left[\frac{\gamma}{\phi c_H}\right]^{\frac{\gamma}{\phi-\gamma}}}{\beta c_n}\right]^{\frac{\phi-\gamma}{(\phi-\gamma)(\beta-\theta)-(\theta-1)\gamma}}$, AI deepens the division of labor but only until the number of specialists reach N, after which it does not have an effect on specialization. As N increases above $\left[\frac{\theta\left[\frac{\gamma}{\phi c_H}\right]^{\frac{\gamma}{\phi-\gamma}}}{\beta c_n}\right]^{\frac{\phi-\gamma}{(\phi-\gamma)(\beta-\theta)-(\theta-1)\gamma}}$, the effect of AI on the division of labor is in full force. Therefore, we can state that increasing the market size and specialization deepening by introducing AI tools are complements as one increases the benefits from the other.

3 Discussion

Naturally, this short essay is only a small contribution to the debates surrounding artificial intelligence. It does not purport to show that this particular understanding of the division of labor between humans and machines would also hold, rather, it argues such an interpretation would provide different predictions, leading to possibly different attitudes toward AI, which is important especially when we consider future AI-related policies and regulations. A criticism of my framework could be that if AI can partially take over the role of generalists, why can't it take over specialized tasks as well? I will answer this objection in two ways. One answer to this retort is that AI can, indeed, increasingly perform more narrowly specialized tasks, but the possibilities of specialization are almost infinite. One can always find a subfield within a field to specialize for. Therefore, if AI "takes over" a specialized field, it may actually increase the productivity of humans to specialize in subfields within that field. To put it in another way, AI has a comparative advantage in being a generalist (even within a specialty), so it would be, at least in my model, always more desirable to employ AI tools in a generalist role, potentially leading to more subspecialties within a specialized field. It is all the more so given that for AI tools to become specialists, they need to be taught the particular specialty, which would need to be done by already specialized humans, who could also act as specialists on their own. The other answer to the objection is the following.

Consider, as we have done throughout the paper, an economy with N individuals and $n < N$ specialist team members. Suppose artificial intelligence can take over specialized fields. If that happens, some workers must remain either idle or become a generalist. Yet, the demand for generalists is limited relative to the demand for specialists. In fact, in my highly stylized model even one generalist can perform the coordination of the whole team and each generalist must be versed in all specialties, no "savings" stem from increasing the number of generalists, compared to increasing the number of specialists. Therefore if AI takes over specialized tasks, at least a fraction of the population will remain idle but that means they can train themselves in any specialty at a very low opportunity cost, which then takes away the advantage of AI relative to humans. AI's advantage in coordination, on the other hand, is more durable given the more limited demand for generalists. One may wonder how much this train of thought is driven by my assumption that one generalist is "enough" for coordination. Suppose then that the "demand" for generalists is downward-sloping, so that additional generalists also have a positive marginal return. Then when AI takes over a fraction of tasks, a certain number of the displaced workers might become generalists. Yet at a certain point the marginal benefit from allocating human labor to coordination or to a specialized task becomes equal. Then if there would still be idle workers, they would replace AI in a fraction of tasks. The larger the difference between the optimal number of tasks (team members) and the optimal number of generalists, the less would AI expand into specialized tasks. That is, there would be a division of labor between AI and human workers, and this will be patterned such that AI would largely be responsible for coordinating the specialists (although not in an entrepreneurial, rather in a general practitioner role) and workers would focus on specialized tasks as well as on acquiring general knowledge that can be used in those tasks, for even if AI had an absolute advantage both as a generalist and as a specialist, its advantage is greater in aggregating different kinds of specialized knowledge, given that AI can divide its "knowledge" across multiple areas in a way that it does not greatly diminish its knowledge per area, something humans are not capable of.

4 Conclusions

This short paper considered a scenario in which artificial intelligence (AI) serves not as a substitute, but as a complement to specialized, as well as to fully general knowledge. To this date, AI tools such as chatGPT mostly enabled the synthesis of often highly specialized knowledge. This role of AI is somewhat similar to that of a general practitioner in health services. Unlike human generalists, AI is able to absorb a larger amount of specific knowledge through its training. For this reason, it can accomplish a coordinating role in specialization, which in turn aids deeper specialization. Because general knowledge (knowledge that is roughly equally valuable to all tasks) is complementary to specific knowledge, investment in general human capital also increases with the introduction of AI, as demand for high-skilled workers increase. In essence, contrary to fears about AI replacing high-skilled workers, in my framework AI makes high-skilled laborers more productive and sought after.

5 References

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